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Three essays on the vulnerability of financial institutions and their strategic reaction to shocks

George T. Overton

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Membre de l'université Paris Lumières

George Overton

Trois essais sur la vulnérabilité des institutions financières et leur réaction stratégique aux chocs

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en vue de l'obtention du doctorat de Sciences économiques de l'Université Paris Nanterre
sous la direction de M. Jean-Pierre Allegret (Université Côte d'Azur)

Jury :

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Acknowledgments

He's going for that anti-marketing dollar. That's a good market. He's very smart.
- Bill Hicks

I think a majority of us who decided to write a thesis in economics did so more out of insecurity about ourselves than out of an unbridled passion for the study of the movement of goods and services. I am squarely average in this regard. For many, it is a pursuit not unlike entering a snail eating contest to find out *just how much* you enjoy snails, because the world might need to know if you *have what it takes* to be in the snail game. Then, perhaps, on the 39th or the 192th or 637th day of eating snails, you may have your doubts about snails. Perhaps you think, well, I enjoy snails, but what am I doing here? You may have friends who just gave birth to a beautiful child, or bought a shiny new car, and they ask you how the snails are going and you begin to consider what the snail people refer to as *counterfactuals*. Perhaps there were other ways to appear sophisticated and French besides five years of snails.

Snails, it turns out, are unexciting and slow. And while perfectly understandable for a shelled gastropod, they do not make for very good companions on the road. For this reason, it is imperative to have a support system that helps you learn, helps you *want* to learn, explains something for the eleventh time, tells you what you want to hear when your head is in the toilet, tolerates your incessant negativity or just makes you feel good. In this regard, luckily, I am far from average.

I'd like to first and foremost thank my thesis advisor, Jean-Pierre, who is accustomed to French George (Georges) and is surprised to encounter an extended metaphor about snails in my thesis. Jean-Pierre has been extremely patient with me through both the lows and the even lower lows of my thesis. I myself often groan about the, well, sluggishness of academics when it comes to communication, and luckily Jean-Pierre bucks this trend. It is a privilege to know that your advisor supports you unconditionally and will provide expertise

and (more importantly) positivity when you feel you are at a dead end. His encouragement and understanding have been instrumental in finishing this thesis. I thank him for agreeing to be my advisor and for helping me along the way.

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To Cam and Augie I want to say, you’re both shameless clods. You are also the two most

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Martin is not a shameless clod, and is two meters tall, otherwise he would have been included in the previous paragraph. Martin has the incredible gift to doubt his ability to do something and then promptly do it, every time. I have drawn more inspiration from him than he knows. *I would be remiss* (in Peter Griffin's voice) to omit him from these acknowledgements as a friend and a fearless learner.

Despite my praise for them, the three gentlemen above are all hapless dumbbells compared to Zahra. I met Zahra in a linear algebra class in 2016, which was somewhat comparable to Bach listening to a class of seventh graders learn Jingle Bells on the recorder. While I have retained probably none of it, Zahra tutored me to a respectable grade in that class, and has since fielded many questions related to concepts about which I still understand essentially nothing. In addition to patiently teaching math to such an innumerate bumpkin as myself, I thank her for all the laughs and wine-fueled political conversations.

I raise a chilled gas station slushy to my oldest friend and fellow fatalistic scholar, John. Unfortunately neither your thesis on radio music in the 1980s nor my thesis on insurance companies can compare to the insight provided by Beavis and Butthead. We can both make peace with this fact, however, imagining the collective spit-take of our middle school teachers if they knew that *those* were the two kids that would eventually become doctors. Thank you for your lifelong friendship and willingness to commiserate over grad school life.

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information and a stalwart supporter of this thesis, despite his skepticism about research.

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Finally, I must thank my family—Mom, Dad, Roseanne and Nellie—who never pressured me to be anything other than who I wanted to be. I admire their capacity to love unconditionally, even if I never say it. I dedicate this thesis to my little sister Nellie, who will only be interested in such a designation if I promise it can be exchanged for a luncheon at Portillo's. It therefore can and will be.

Trois essais sur la vulnérabilité des institutions financières et leur réaction stratégique aux chocs

Résumé

Le secteur des assurances joue un rôle crucial dans les économies avancées comme dans les économies en voie de développement. Les vagues de faillites au Japon dans les années 1990 au sein de ce secteur, ainsi que les renflouements à grande échelle dans le sillage de la crise financière de 2008, ont démontré la vulnérabilité de cette industrie aux chocs macroéconomiques.

Dans cette thèse, d'abord nous construisons une base de données unique sur les défaillances d'assurance dans quatre grands pays au cours des 40 dernières années. Nos résultats montrent que la présence d'actifs à revenu fixe dans le portefeuille joue un rôle d'atténuation du risque pour les sociétés d'assurance-vie, tandis que cet effet n'est pas présent pour les organismes du secteur non-vie. Inversement, nous trouvons des preuves que l'efficacité opérationnelle est importante pour les organismes d'assurance non-vie, mais pas pour le secteur vie. Dans notre deuxième chapitre, nous dévoilons des incitations à la fusion créées par Solvabilité II, ainsi qu'une série de réformes spécifiques à la France. Nos résultats suggèrent une absence d'arbitrage réglementaire lié à la conception de Solvabilité II. De plus, contrairement aux autres organismes cibles, les assureurs exposés aux réformes du secteur de la santé n'ont pas été confrontés à des problèmes de rentabilité ou de solvabilité au moment de leur fusion, indiquant une anticipation des effets de la réforme avant leur matérialisation. Enfin, nous quantifions l'effet de la politique monétaire sur la probabilité de faire défaut sur un crédit immobilier à taux variable. En particulier, nos résultats révèlent qu'une augmentation de 100 pb des paiements trimestriels induite par les variations de l'Euribor 3 mois augmente la probabilité de défaut d'environ 5%.

Mots Clés : Insolvabilité des assurances, prédiction de défaut, fusions et acquisitions, réformes réglementaires, transmission de la politique monétaire

Three essays on the vulnerability of financial institutions and their strategic reaction to shocks

Abstract

The insurance industry plays a crucial role in both developing and advanced economies. Waves of failures in Japan in the 1990s as well as large-scale bailouts in the wake of the Great Recession demonstrated the vulnerability of this industry to macroeconomic shocks.

In this thesis, we first construct a unique data-set of insurance failures in four large countries over the last 40 years. Our estimates show that portfolio composition (particularly, the presence of fixed income instruments) plays a risk-mitigating role for life insurance firms, while no such effect appears for non-life firms. Conversely, we find evidence that operating efficiency matters for non-life firms, but not life sector firms. In our second chapter, we discuss the merger incentives provided by Solvency II, as well as a series of French-specific health sector reforms. Our results suggest an absence of regulatory arbitrage linked to the design of Solvency II. Further, unlike other target undertakings, insurers exposed to the health-sector reforms were not experiencing profitability or solvency problems at the time of their merger, indicating an anticipation of the reform's effects before their materialization. Finally, in our last chapter, we quantify the extent to which monetary policy asymmetrically affects variable-rate mortgages. In particular, our results reveal that a 100 bp increase in quarterly payment induced by variations in the 3-month Euribor increases the probability of default by around 5%.

Keywords: Insurance insolvency, default prediction, mergers and acquisitions, regulatory reform, monetary policy transmission

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Introduction

Les organismes d'assurance jouent un rôle fondamental dans la gestion des risques au sein des économies. [Arena \(2008\)](#) montre comment la présence d'activité en assurance vie et non-vie a un impact positif sur la croissance économique dans 56 pays. Les effets bénéfiques des marchés d'assurance robustes sont nombreux et varient selon les juridictions. Lorsqu'ils intègrent les pays en développement, ces marchés permettent souvent de mutualiser les risques et facilitent les transactions pour les agents averses au risque. Ils servent également à stabiliser les revenus des ménages, en plus de jouer un rôle clé en tant qu'intermédiaire financier. En tant que premier marché de l'assurance en Europe continentale¹, la France est particulièrement dépendante de ce secteur. En 2019, les assureurs français ont souscrit €150 milliards de primes d'assurance-vie, €109 milliards de primes non-vie, supportant ensemble €3.02 trillions d'actifs totaux. Avec un ratio de solvabilité de 267% à l'échelle du marché, les organismes ont été plus que capables de faire face aux perturbations financières, même pendant le cycle de la crise économique de Covid-19.

Parmi les assureurs français, figure un groupe d'importance systémique, auquel s'ajoutent d'autres assureurs de taille importante appartenant à des groupes bancaires (ainsi appelés *bancassureurs*). Le débat s'intensifie entre les décideurs et les universitaires concernant le caractère systémique des marchés de l'assurance. Étant donné que les architectes de la politique macroprudentielle sont chargés de comprendre les liens d'un système financier de plus en plus complexe et interdépendant, les assureurs accordent une attention renouvelée aux activités spécifiques liées aux entreprises. Un volet de la littérature universitaire (voir [Harrington \(2009\)](#), [Billio et al. \(2012\)](#) ou [Cummins and Weiss \(2014\)](#)) soutient l'idée que ces entreprises sont exposées au risque de marché émanant d'autres institutions (telles que les banques), bien qu'elles ne soient pas ou peu susceptibles de provoquer à elles seules un événement d'instabilité financière. Les assureurs vie sont typiquement considérés comme vulnérables aux crises intra-sectorielles en raison du risque de levier et de liquidité, tandis que les assureurs non-vie et dommages sont vulnérables aux crises de réassurance résultant

¹ACPR (2019)

de l'exposition au crédit de la contrepartie. Surtout, ce sont les activités “non essentielles” (telles que la vente de produits dérivés) qui auraient le potentiel de causer un événement systémique, à l'instar des instruments de credit default swaps (CDS) vendus par le groupe américain AIG avant la crise financière de 2007-2008. Dans l'ensemble, cependant, à quelques exceptions près, comme le groupe néerlandais Aegon, le secteur de l'assurance est resté à la périphérie de cette crise.

Toutefois, les faillites de groupes d'assurance japonais dans les années 90 (voir [Bernard et al. \(2014\)](#)) et pendant la crise financière de 2008, ainsi que les difficultés du groupe américain AIG, ont montré que ces institutions étaient vulnérables aux chocs. En 2010, le Conseil de stabilité financière (FSB) a demandé à l'Association internationale des contrôleurs d'assurance (IAIS) d'élaborer un processus pour identifier les groupes d'assurance à l'échelle mondiale dont la détresse ou la défaillance désordonnée, en raison de leur taille, de leur complexité et de leur interconnexion, entraîneraient des perturbations du système financier mondial et de l'activité économique. Une première méthodologie est développée et publiée en 2013, avant d'être appliquée pour l'identification des “Globally Systemically Important Insurers” (G-SIIs) en 2013, 2014 et 2015. Au cœur de cette méthodologie se trouve une approche basée sur les activités, qui donne plus de poids aux activités dites “non traditionnelles, non-assurance” (NTNI) pour les raisons évoquées ci-dessus. En novembre 2019, l'IAIS a adopté le “cadre holistique” pour l'évaluation et l'atténuation du risque systémique dans le secteur de l'assurance, fondé sur un exercice récurrent de surveillance mondiale qui vise à limiter l'accumulation du risque systémique *ex ante*.

L'identification d'indicateurs avancés—l'objectif du premier article de cette thèse—reste important dans une perspective microprudentielle (conformément au mandat de l'Autorité de Contrôle Prudentiel et de Résolution, l'institution d'accueil dans le cadre de cette thèse) indépendamment du potentiel d'effets de contagion. Une supervision appropriée ainsi qu'une intervention rapide peuvent à la fois maintenir la confiance des consommateurs et protéger les assurés en cas d'un éventuel transfert de portefeuille ou liquidation. En 2014, l'Autorité européenne des assurances et des pensions professionnelles (EIOPA) a commencé à collecter des informations sur les défaillances ou les “quasi-défaillances” d'organismes d'assurance au sein de l'Espace économique européen. Cette base de données, qui comprend 180 cas entre 1999 et 2016, vise à comprendre à la fois les causes probables ainsi que leur impact plus général au sein du marché national concerné. Le rapport analytique (publié en 2018) a donné plusieurs conclusions importantes. Premièrement, il a révélé que le risque le plus courant concernait des problèmes internes ou des contraintes de gouvernance qui sont difficiles à

définir ou même à repérer, comme la capacité de gestion. Ces éléments sont problématiques pour le superviseur ; même si les diverses dimensions du Pilier II de Solvabilité II cherchent à renforcer la gouvernance et la gestion des risques, la supervision reste essentiellement quantitative et axée sur les données. Un deuxième point à retenir de cette étude est le manque de corrélation forte des défaillances avec les cycles économiques: seulement 37% des déficiences du secteur de la vie sous la fenêtre d'étude de 17 ans se sont produites pendant la période 2008-2009. Ensemble, ces résultats appellent à une meilleure compréhension de la dynamique des défaillances d'assurance, en particulier dans un contexte d'incertitude macroéconomique persistante. Tel est l'objectif du premier chapitre de cette thèse.

En outre, la concurrence des institutions financières au sein de l'Espace économique européen n'a cessé de s'intensifier, laissant potentiellement les entreprises encore plus vulnérables aux chocs. En effet, un processus d'intégration est observée depuis un certain nombre de mesures phares qui visaient à unifier ce marché, autrefois caractérisé par des marchés nationaux souvent "protégés" avec une forte fragmentation nationale. Suite à l'introduction de plusieurs directives sur les assurances entre 1987 et 1994 permettant aux compagnies d'assurance de concevoir leurs produits et d'exercer une activité dans tout l'Espace économique européen sous une licence unique, ce marché a en effet connu une transformation importante. Les évaluations initiales de ce changement dans la structure du marché ont révélé une convergence de l'inefficacité des firmes à travers des frontières (voir [Mahlberg and Url \(2000\)](#) ou [Beckmann et al. \(2003\)](#)) ainsi qu'une intégration accrue du marché. Cette tendance est également confirmée par des études ultérieures (par exemple, [Cummins et al. \(2017\)](#)).

L'harmonisation entre les pays de l'Union européenne s'est poursuivie en 2016 avec l'entrée en vigueur des réformes réglementaires Solvabilité II, qui ont transformé la surveillance du secteur assurantiel en un régime fondé sur les risques et cohérent avec le marché ("*market-consistent*"). Le cadre précédent ("*Solvabilité I*")—fondé sur une directive européenne de 1973 pour l'assurance non-vie et de 1979 pour l'assurance vie—avait le mérite d'homogénéiser les principes réglementaires au sein du marché européen, mais reposait sur des exigences de fonds propres trop simplistes qui ne reflétaient pas les véritables expositions (ou mécanismes de diversification) auxquelles était confronté un assureur donné.

La question des effets plus importants de cette régulation reste peu étudiée dans la littérature et fait donc l'objet du deuxième chapitre de cette thèse. En effet, en réaction à la directive Solvabilité II de 2009, de nombreux observateurs pensaient que cette harmonisation et cette convergence transfrontalière donneraient lieu à un phénomène distinct : la

concentration. Alors que le principe de la libre prestation de services du marché unique de l'UE peut, en théorie, supprimer certaines barrières pour des bases de clients plus larges, les acteurs plus importants peuvent bénéficier de rendements d'échelle croissants pour mieux tarifier les plus petits organismes—en particulier ceux qui ne sont pas en mesure de supporter les coûts de mise en conformité associés au nouveau régime réglementaire Solvabilité II.

Outre la réforme précitée, le marché français a également connu une transformation réglementaire dans un secteur d'activité spécifique: les contrats de complémentaire de santé. L'accord national interprofessionnel (ANI)—signé en 2013 avant d'entrer en vigueur en 2016—oblige tout employeur à proposer des contrats individuels ou collectifs à chaque salarié. Parallèlement, une clause dite de désignation a été déclarée inconstitutionnelle avant d'être supprimée² du projet de loi ANI. Ensemble, ces réformes ont élargi le marché et ont intensifié la concurrence entre les acteurs, exerçant une pression soutenue sur les entreprises ayant des liens historiquement protégés avec des industries données.

Ces évolutions réglementaires ont effectivement coïncidé avec une décroissance du nombre d'organismes d'assurance actifs en France. Entre 2011 et 2019—période au cours de laquelle les réformes ont d'abord été négociées avant d'entrer en vigueur—le nombre total d'entreprises d'assurance agréées sur le marché français est passé de 1 074 à 695. Il est essentiel, tant pour les autorités de la concurrence que pour les superviseurs pruden- tiels, de comprendre la nature de ces fusions-acquisitions. D'une part, les gains d'efficacité associés aux grandes firmes peuvent dans certains cas être répercutés sur les consommateurs sur le marché des produits; en revanche, une concentration plus élevée entraîne souvent des prix (primes) plus élevés (voir, par exemple, [Trish and Herring \(2015\)](#) pour une étude sur le marché de l'assurance santé aux États-Unis). D'autre part, au-delà de la question de la concentration du marché, nous pouvons tester la présence d'un arbitrage réglementaire potentiel et documenter les effets indésirables de ces réformes qui ont transformé le secteur de l'assurance au cours de la dernière décennie.

Enfin, le troisième chapitre de cette thèse redécouvre le thème de la prédiction de défaut abordé dans le premier article, appliqué cette fois aux prêts immobiliers. Parallèlement aux contrats d'assurance vie et non-vie, les prêts au logement constituent une interconnexion importante des ménages dans le système financier. La dette immobilière est effectivement la

²Le groupe de sénateurs UMP qui a adapté la législation ANI pour supprimer la clause de désignation a estimé qu'elle "serait de nature à entraver le libre jeu de la concurrence entre les différents organismes d'assurance." [Dispofi \(2015\)](#)

principale source d'endettement des ménages dans tous les pays de la zone euro (voir [Finance and Network \(2016\)](#)). De plus, une relation de crédit à long terme implique des frais de logement récurrents, qui représentent une part importante du budget mensuel d'un ménage. La situation financière est donc très dépendante des conditions de crédit, notamment des taux d'intérêt. Par conséquent, ces taux ont un impact important sur les contraintes budgétaires, l'épargne, la consommation et l'accumulation de richesse au cours de leur cycle de vie. Dans cet article, une analyse est donc menée sur l'interaction entre la fragilité financière des ménages et la politique monétaire.

Les taux d'intérêt sur les prêts immobiliers proposés aux ménages français ont fortement baissé au cours des dernières décennies, passant de 6% au début des années 2000 à un record historiquement bas de 1,2% fin 2019,³ grâce à l'action de la politique monétaire expansionniste de la BCE. Cet environnement a largement facilité l'accès à l'achat du logement, stimulant la demande de crédit dans ce secteur.

Comme mentionné ci-dessus, les taux d'intérêt sont le principal canal de transmission directe de la politique monétaire aux finances des ménages. Ainsi, la politique monétaire expansionniste a des effets directs sur le coût du capital pour les nouveaux emprunteurs, qui bénéficient d'une amélioration des conditions d'octroi de leurs crédits immobiliers. Il existe, cependant, une hétérogénéité quant à la façon dont les cohortes de prêts existantes sont exposées à ce canal de transmission de la politique monétaire. En effet, les taux directeurs ont un impact sur les paiements d'intérêts pour les ménages ayant des dettes immobilières en cours (ainsi que les ménages ayant des actifs à court terme ([Ampudia et al. \(2018\)](#))). Alors que les détenteurs de prêts à taux fixe ne voient aucun changement, ces ménages qui ont souscrit un prêt à taux flottant peuvent gagner en pouvoir d'achat suite à une réduction des taux directeurs.

7% du stock de crédits immobiliers en cours en France suivent des échéances révisables ou variables, même si 97% des nouveaux crédits en France sont à taux fixe ([ACPR \(2017\)](#)). En fonction du contexte macroéconomique, certains emprunteurs peuvent choisir de refinancer leur prêts pour réduire les remboursements futurs et, in fine, minimiser les coûts d'investissement. Cette stratégie a été particulièrement pratiquée entre 2016 et 2017 en France, où environ 30% des nouveaux prêts étaient des renégociations de contrats existants. Cependant, [Mian et al. \(2013\)](#) montrent que les ménages très endettés sont souvent incapables de refinancer leur emprunt à un taux inférieur en raison de leur situation financière

³Banque de France, nouveaux crédits immobiliers aux particuliers, annuel taux d'intérêt.

vulnérable. Cela peut empêcher les ménages de certaines catégories socio-professionnelles de bénéficier des conditions favorables sur le marché du crédit. En conséquence, il existe d'importantes frictions de transmission de la politique monétaire vers le stock de prêts au logement en raison de la prédominance des prêts à taux fixe et de la capacité de refinancement limitée pour les ménages très endettés. Ainsi, une partie fragile de la population reste exposée aux futurs changements de politique monétaire.

Compte tenu de l'environnement actuel de taux d'intérêt extrêmement bas, il est naturel de s'interroger sur la future hausse attendue des taux directeurs. L'effondrement de Countrywide Financial en 2008 a montré qu'une augmentation des paiements sur les prêts sophistiqués peut déclencher une vague de défauts. Par conséquent, certaines questions se posent aujourd'hui quant à l'effet négatif direct qu'un changement sur les taux directeurs pourrait avoir dans un avenir proche, surtout dans les pays où les prêts à taux variable dominent le marché.

Présentation et organisation de la thèse

Le marché européen de l'assurance (*et, a fortiori*, le marché français) s'est profondément transformé au cours de la dernière décennie. Suite à la mise en place du marché unique européen, la concurrence transfrontalière a renforcé la nécessité d'un cadre prudentiel unifié. Après environ une décennie de négociations, la réforme Solvabilité II est entrée en vigueur, harmonisant les pratiques mais coïncidant avec une vague de fusions—en particulier parmi les petites entreprises. Parallèlement, une série de fusions spécifiques à la France dans des secteurs ciblés a encore accru la concurrence intermarchés, accentuant la tendance à élargir la taille des marchés et le choix des consommateurs.

Notre thèse s'inscrit dans ce contexte et cherche à comprendre les effets de ces réformes et à évaluer les déterminants des vulnérabilités dans ce secteur tout en tenant compte de l'évolution des contextes juridiques. Nous projetons également l'étude des déterminants du défaut sur un secteur spécifique—celui des prêts au logement. A l'instar du chapitre qui étudie les organismes d'assurance, nous utilisons une base de données unique pour essayer de démêler les contributeurs macroéconomiques au défaut des caractéristiques idiosyncratiques. En effet, il est important aujourd'hui de comprendre les répercussions—ou l'absence de celles-ci— des chocs macroéconomiques sur la fragilité financière des entreprises et des ménages, car des incertitudes persistent quant à la croissance économique future et aux

changements à venir de la politique monétaire.

Le premier chapitre vise à identifier les mécanismes de l’insolvabilité des assurances dans différentes juridictions à l’aide d’une base de données unique assemblée à la main. En raison de ce que l’on appelle “l’inversion du cycle de production” dans le secteur des assurances, les faillites surviennent souvent en raison de décisions de gestion prises des années en amont de la manifestation d’une défaillance. Ce chapitre explore cette question en mettant en évidence les différentes dynamiques du défaut selon les secteurs ainsi que selon les pays.

Ensuite, le deuxième chapitre analyse deux réformes réglementaires qui ont transformé le marché français de l’assurance. Nous montrons que la conception de chaque réforme a donné des incitations distinctes à l’activité de fusion-acquisition, selon les branches d’activités d’un organisme. En effet, au cours de la dernière décennie, le nombre d’entreprises agréées en France diminué d’un tiers. Ce chapitre révèle donc le rôle de la fragilité financière concernant la probabilité d’être impliqué dans une fusion, et il explore également le potentiel d’arbitrage réglementaire.

Enfin, le dernier chapitre a pour objectif de quantifier la mesure dans laquelle la nature d’un crédit immobilier expose les ménages à une vulnérabilité financière à travers le risque de taux d’intérêt. Cette question revêt aujourd’hui une importance accrue—en particulier dans les juridictions où les instruments à taux variable détiennent une part de marché plus élevée—étant donné l’incertitude quant à la persistance des mesures dites “d’assouplissement quantitatif” prises par les banques centrales en réponse à la crise du Covid-19.

Différences sectorielles sur les marchés assurantiels

Ce chapitre aborde la question des défaillances des organismes d’assurances en estimant un nombre d’indicateurs avancés à partir d’une base de données unique sur quatre pays développés. Le secteur de l’assurance est une composante essentielle du système financier au niveau international, ainsi la défaillance d’une firme est souvent plus coûteuse en comparaison à d’autres institutions financières (voir [Grace et al. \(2003\)](#)). De plus, en finançant l’économie réelle par des investissements à long terme et en facilitant la mutualisation des risques entre les différents assurés, l’assurance contribue à la croissance des secteurs financier et non financier. Compte tenu de l’importance de ces fonctions clés, la prévention de l’insolvabilité dans le secteur de l’assurance constitue une mission complexe mais essentielle du contrôle

prudentiel.

Plantin and Rochet (2007) ainsi que EIOPA (2018) montrent que la faillite des compagnies d'assurance est souvent due à une mauvaise prise de décision—allant de la négligence à la fraude—plusieurs années avant la faillite proprement dite. L'existence d'une dynamique particulière au sein de ce secteur peut en être la cause; en effet, une entreprise d'assurance reçoit une prime en amont de la matérialisation du risque couvert, c'est-à-dire du service effectué. Cette "inversion du cycle de production" est un des mécanismes essentiels sous-jacents à la plupart des opérations d'assurance par lesquelles les entreprises peuvent être amenées à des prises de risques non-soutenables sur le long-terme. Ce décalage des incitations peut s'avérer problématique en termes de stabilité financière.

D'autres mécanismes peuvent également entraîner la faillite d'un assureur, comme une mauvaise gestion, une composition de portefeuille risquée, une croissance rapide ou instable, et des conditions macroéconomiques. La cause des difficultés diffère souvent selon la ligne d'activité de l'assureur en question—une dimension importante qui constitue un apport du premier chapitre de cette thèse. Aujourd'hui, le risque d'insolvabilité des compagnies d'assurance pourrait se manifester à nouveau, dans la mesure où les assurances sont confrontées à une pression et à une incertitude accrue dans un contexte de taux d'intérêt bas (ou négatifs), ainsi qu'à l'émergence de nouveaux risques, y compris ceux liés au changement climatique et à la Covid-19. L'objectif de cet article est donc d'enrichir la littérature sur la prévision des défaillances d'assurance en déterminant des indicateurs avancés ou des facteurs contributifs qui peuvent aider les autorités de supervision à identifier les vulnérabilités et à agir en conséquence, afin de réduire les conséquences négatives d'une défaillance.

Les apports de cet article sont nombreux. Tout d'abord, nous avons assemblé une base de données internationale qui fusionne les données relatives aux bilans et aux comptes de résultats ainsi que des informations sur 263 cas de défaillance de compagnies d'assurance aux États-Unis, au Royaume-Uni, au Japon et en France au cours des 30 dernières années. Ces cas de faillites sont comparés à un panel beaucoup plus large d'institutions solvables dans ces pays sur la même période. Ensuite, contrairement à de nombreux travaux qui ne traitent souvent qu'un seul secteur, le chapitre analyse les spécificités des défaillances des secteurs vie et non-vie et constate des différences dans la dynamique de leurs insolvabilités. En utilisant différentes spécifications de type logit à effet fixe et des modèles de survie paramétriques, ces analyses fournissent la preuve que la nature des actifs joue un rôle déterminant dans la prévision des défaillances d'assurance vie, tandis que le compte de résultat est le critère clé

pour les assureurs non-vie. Par ailleurs, l'article met en évidence des différences à travers les pays : nos résultats suggèrent un rôle plus important de l'inefficacité opérationnelle en assurance non-vie en France et un impact moins positif de l'investissement en dette en assurance vie au Japon. Ces deux résultats sont liés à des différences de fonctionnement des juridictions nationales que nous expliquons en détail à l'aide des études de la littérature juridique.

La composition des actifs (telle que mesurée par la part des instruments à revenu fixe dans le portefeuille d'investissement total) prédit de manière statistiquement significative la défaillance des assureurs vie, tandis que l'(in-)efficacité opérationnelle (frais d'exploitation et d'administration sur le total des primes émises) ne semble jouer aucun rôle. Le contraire est vrai dans le secteur non-vie: la composition des actifs—très importante dans le secteur vie—semble ne jouer aucun rôle dans le secteur non-vie, tandis que l'efficacité opérationnelle est un prédicteur important de défaillance pour toutes les spécifications. La rentabilité (mesurée par le ROA) prédit les défaillances jusqu'à trois ans à l'avance dans le secteur non-vie, mais seulement un an à l'avance dans le secteur vie, ce qui peut s'interpréter comme une indication que l'effet des chocs négatifs sur la rentabilité diminue à mesure que la durée d'engagement augmente. L'article vérifie aussi que, sur cet échantillon, les entreprises d'assurance de petite taille ont un risque de défaut plus important que les plus grandes—un résultat qui est confirmé dans [EIOPA \(2018\)](#). Tous ces résultats ont des implications pour la mise en œuvre du contrôle prudentiel que nous aborderons en conclusion.

Réforme réglementaire et structure du marché

Ce chapitre étudie la structure du marché français de l'assurance, et sa transformation au cours de la dernière décennie suite à l'introduction d'une série de réformes réglementaires. Ces dernières ont impacté de manière hétérogène différentes branches d'activité et, par conséquent, ont donné des incitations uniques à effectuer des activités de fusion-acquisition en fonction de la spécialisation de différents organismes.

Nous montrons d'abord la diminution significative du nombre d'organismes depuis le début de notre échantillon (précisément, une baisse de l'ordre de 35% des assureurs agréés de 2011 à 2019). Cependant, en raison des parts de marché modestes de ces firmes, les indices de concentration du marché dans la quasi-totalité des métiers restent très faibles et présentent peu de variation tout au long de l'historique de l'échantillon.

Nous discutons ensuite des répercussions des différentes réformes, en commençant par les incitations aux fusions et acquisitions données par Solvabilité II. Deux types de fusions sous Solvabilité II peuvent être imaginés. Si les coûts de mise en conformité ont une composante de coût fixe, les assureurs de petite taille par rapport à la moyenne du marché pourraient être affectés de manière asymétrique étant donné le seuil d'éligibilité bas (€5 million de primes ou €25 million de provisions techniques). Par conséquent, on pourrait s'attendre à ce que des fusions se produisent entre des organismes similaires—c'est-à-dire des assureurs exerçant les mêmes activités—afin de combiner plus efficacement les coûts fixes et de réaliser des économies d'échelle. Par ailleurs, comme la formule standard récompense une diversification des expositions aux différents modules risques, cette réforme pourrait conduire précisément au type de fusion inverse : afin de profiter d'un effet de diversification dans la réglementation, un assureur pourrait être tenté de fusionner avec un assureur spécialisé dans *différentes* branches d'activité (ou ayant des expositions aux risques différentes des siennes). Nos données reflètent une prédominance des fusions “traditionnelles”, c'est-à-dire celles qui cherchent à réaliser des économies d'échelle dans des secteurs d'activité similaires. Ceci est cohérent avec une absence d'arbitrage réglementaire.

Nous analysons ensuite une réforme spécifique à la santé (la loi ANI) et constatons une forte vague de fusions dans ce secteur. En utilisant une nouvelle base de données de 256 fusions au sein du marché français de 2011 à 2019—et en exploitant le fait que seul un segment du marché français était exposé à cette loi, contrairement à Solvabilité II—nous montrons que les organismes cibles dans ce métier n'ont pas été motivés par des soucis de rentabilité ou de solvabilité, à la différence des fusions au sein d'autres branches d'activité. Ce résultat est cohérent avec le fait que les entreprises anticipent la réforme avant la matérialisation de ses conséquences.

Transmission de la politique monétaire aux ménages

Dans ce troisième chapitre, nous évaluons la transmission de la politique monétaire aux ménages à travers un canal particulier: les mensualités sur les prêts immobiliers à taux variables. En effet, une variation du taux directeur génère des mouvements asymétriques dans la partie variable de ces paiements qui, à leur tour, affectent la probabilité de défaut de l'emprunteur. Précisément, sur la période 2004-2015, nous cherchons à quantifier l'effet d'un choc sur le montant des paiements (induit par un changement de politique monétaire)

sur la propension d'un ménage à faire défaut sur son prêt immobilier. Nous analysons également le rôle de la stabilité de l'emploi et de la classe socio-économique, en exploitant une base de données propriétaire d'environ 5 millions de lignes de crédit au logement accordées aux ménages sur le marché français entre 1994 et 2015. Afin de mesurer les chocs de politique monétaire, nous reconstruisons des tableaux d'amortissement théoriques pour toutes les lignes de crédit de notre échantillon, en décomposant les mensualités pour isoler la composante en intérêts.

De plus, certaines caractéristiques uniques de nos données et de notre juridiction nationale nous permettent d'isoler les défaillances involontaires ou stratégiques, ce qui constitue un intérêt supplémentaire de notre étude pour la littérature académique. Par ailleurs, comme nous observons de manière exogène des notes de risque de crédit (calculées de manière cohérente par une institution tierce) et des caractéristiques exhaustives supplémentaires des ménages, nous sommes en mesure de comparer les profils de risque des emprunteurs pairs ou quasi-pairs qui sont différemment exposés aux chocs de politique monétaire en fonction de leur type de prêt (taux ajustable contre taux fixe).

Notre étude a plusieurs attributs inédits. Tout d'abord, ce papier est, à notre connaissance, le premier à évaluer les effets de la politique monétaire sur le défaut immobilier pour la juridiction française (le second pour l'Europe). Ceci est particulièrement important dans l'environnement actuel de taux d'intérêt extrêmement bas et d'incertitude quant aux variations futures (rehausses, notamment). Deuxièmement, nous exploitons une base exhaustive dans laquelle le défaut stratégique est effectivement absent, isolant ainsi mieux l'effet sur le défaut non-volontaire. Les conséquences de cette isolation sur nos estimations sont probablement matérielles; dans une étude américaine, [Gerardi et al. \(2017\)](#) constatent que 38% des ménages en défaut sont capables d'effectuer leurs versements hypothécaires sans réduire leur consommation. Les différences propres à la juridiction française offrent ainsi une opportunité unique de se pencher sur la fragilité financière des ménages, ce qui distingue notre étude par rapport à la littérature précédente.

Troisièmement, nous utilisons une base de données exceptionnellement grande, couvrant la durée de vie de près de 5 millions de prêts en France. Cette information très granulaire nous permet de saisir la fragilité financière (et d'autres caractéristiques) spécifique aux ménages, ainsi que d'autres facteurs qui pourraient motiver un ménage à souscrire un type de prêt plutôt qu'un autre. En conséquence, nous sommes en mesure de comparer l'exposition des prêts fixes et ajustables à l'intervention de la politique monétaire, tout en limitant le

problème de sélection. Enfin, notre étude peut donner un aperçu de la situation des pays européens voisins (avec des institutions par ailleurs similaires) où les prêts à taux variable sont plus répandus, où les institutions financières favorisent davantage leur adoption (voir [Albertazzi et al. \(2018\)](#)).

Ce chapitre apporte de multiples résultats à la littérature. Dans un premier temps, ces travaux documentent les effets asymétriques des changements de taux directeurs sur la stabilité financière des emprunteurs de logements en cours. Nous constatons qu’une hausse de 1pp des taux d’intérêt augmente la probabilité de défaut des ménages de 45%. Ce résultat correspond à des défauts non stratégiques et ne concerne que les emprunteurs à taux variable ou “flottant”, dont les mensualités fluctuent avec les taux directeurs. De plus, nous confirmons le rôle important de la stabilité de l’emploi contre les épisodes de défaut, en particulier pendant les périodes de politique monétaire restrictive.

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Chapter 1

Why Do Insurers Fail? A Comparison of Life and Non-life Insolvencies Using a New International Database

Abstract

Plantin and Rochet (2007) document how insurers often engage in risk-shifting years before the materialization of a failure. This paper empirically examines this claim by testing the mechanisms of insurance insolvency across different jurisdictions, using a first-of-its-kind international database assembled by the authors which merges data on balance sheet and income statements together with information on impairments over the last 30 years in four big countries (France, Japan, the UK and the US). Employing different fixed effects logistic specifications and parametric survival models, the paper presents evidence of profitability as a leading indicator of failures, as well as the higher likelihood of failure by smaller firms. Further, we find an intrinsic asymmetry between the life and non-life insurance sectors. In the life sector, asset mix is highly significant in predicting an impairment, while operating inefficiency plays no role. In the non-life sector, the opposite proves true. Moreover, the paper highlights differences across countries: we note a stronger reaction to operational inefficiency in non-life insurance in France and a less positive impact of debt investment in life insurance in Japan. Both results are linked to differences in the functioning of insurance markets.

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1 Introduction

As highlighted in [Plantin and Rochet \(2007\)](#), the failure of insurance companies often takes place due to bad decision making—ranging from negligent to fraudulent—several years preceding an actual failure. This issue, which stems from the so-called “inversion of the production cycle” in insurance (whereby firms collect premiums in advance of the realization of risks and the disbursement of funds to customers), is problematic from a supervisory point of view. Indeed, when insurers do fail, insolvency is quite costly; the resolution of an insurance company is three to five times more expensive than that of other financial institutions (see [Grace et al. \(2003\)](#)). Are there differences across countries in terms of supervisors’ ability to identify doomed insurers before it is too late?

While historically less exposed to systemic crises, it was an insurer (AIG) who was at the center of a \$200 billion rescue package from the United States government in the immediate aftermath of the 2007-2008 financial crisis. Additionally, Dutch insurer Aegon required a \$3.7 billion bailout from its government during the same period, while a dangerous wave of life insurance failures helped magnify financial shocks in Japan following the Lost Decade. Today, the question of insurance insolvency has regained relevance as undertakings face increased pressure and uncertainty in the low (or negative) interest rate environment. The International Association of Insurance Supervisors (IAIS) has continued its pursuit of a formula for the identification of Globally Systemically Important Insurers (G-SIIs); new methodologies were released in 2013 and 2016 (see [IAIS \(2016\)](#)). Further, the emergence of new threats from climate change, which is projected to increase the frequency and severity of extreme weather events,¹ has captured the attention of insurers and policymakers within the financial system.

Still, the debate surrounding the systemic contribution of insurance remains open. [Harrington \(2009\)](#) emphasizes the lack of systemic footprint in traditional insurance activities, while [Mühlnickel and Weiß \(2015\)](#) demonstrates the systemic significance of mergers, non-traditional financing activities and business line diversification. While insurance liabilities are less “runnable” compared with banking, insurance risks do nonetheless exhibit some correlation with economic cycles. In the property and casualty sector, risk protection decreases during recessions, potentially driving up claims from policyholders. In the life insurance sector, surrenders are affected by the macroeconomic environment (see, e.g., [Geneva Association \(2012\)](#)), increasing during adverse economic conditions (the emergency fund theory relates surrenders to higher unemployment). In addition, upward shocks to long-term interest rates

¹Several insurance defaults have been associated with natural catastrophes, such as Hurricane Andrew in the US in 1992.

lead policyholders to look for higher alternative returns at times where insurers themselves face capital losses on their fixed income portfolios. In the presence of such behavior, microprudential intervention becomes more important to help prevent contagion effects from spreading across firms.

In 2018, the European Insurance and Occupational Pensions Authority (EIOPA) published a study which utilizes questionnaire survey responses from 31 national supervisory authorities to understand the presumed cause of 180 cases of fragility or “near-misses” in different European jurisdictions (see [EIOPA \(2018\)](#)). The mostly qualitative work documents how, in the non-life sector, the top declared risks involve the evaluation of technical provisions, corporate governance and management. In the life sector, the top three reported risks are management, investment risk and market risk—in line with the literature’s emphasis on the linkages between life insurance and financial markets. Most events occur during or after the financial crisis of 2007-2008. Only 48% of cases represent failed firms, including firms that have been partially resolved.

In addition, in the academic and policy debate, very few papers investigate to what extent regulatory frameworks over the world may explain certain differences in terms of insurance insolvencies. While US insolvencies are well-documented, the question remains less studied outside of the US and when monographs are available on certain jurisdictions, either actual defaults are unknown and the explained variable is the solvency ratio (e.g., [Rauch and Wende \(2015\)](#) for Germany, and [Chen and Wong \(2004\)](#) for Asia) or they fail to compare with other regions ([Eling and Jia \(2018\)](#) concentrate on the EU only).

An important contribution of the paper is the construction of an international database of insurance failures, to which we apply several empirical strategies and provide some explanations for differences across countries. Our database is larger than those produced by the insurance insolvency prediction literature. [EIOPA \(2018\)](#) contains 180 EU cases from 1999-2016, while [Leverty and Grace \(2012\)](#) contains 256 U.S. cases from 1989-2000. In comparison, our database includes 437 impairment cases in four big countries (France, Japan, the UK and the US). [Eling and Jia \(2018\)](#) use a large insolvency database composed of both life and non-life insurers, but concentrates on Europe and includes several small countries with specific insurance systems (Denmark, Ireland, etc). We use our database to test a certain number of hypotheses on how these events take place, which helps predict future insurance failures on the basis of available financial data, highlighting similarities and differences between countries.

In the paper, we investigate several dynamics and intuitions provided by previous literature, including some case studies, regarding the relative importance of the asset and liability sides of an insurer’s balance sheet for the sake of forecasting its default—and how

this changes across sectors and countries. We additionally contribute to the evaluation of the potential impact of supervision, in the sense that we measure the true predictive power of the indicators collected by supervisors vis-à-vis future defaults. We find evidence that while such indicators matter, their predictive power changes depending on the nature of the business at hand, and the country in which a firm operates.

In addition to the construction of our database, the second major contribution of the paper to the literature is to confirm practitioners' and supervisors' view—which had never been clearly verified by the academic literature for failure prediction in insurance—that life and non-life sectors behave very differently, with portfolio choice having an important impact for life and operational inefficiency in non-life. We are able to better highlight these differences by separating analysis by sector using a single, common database. Further, we find that macroeconomic variables do not play a very significant role in determining insolvency. The significance of determinants, moreover, varies across jurisdictions: operating inefficiency appears more critical in French jurisdiction, while the asset composition (debt instruments) did not afford the same protection as elsewhere with respect to Japanese insurance failures.

Finally, we acknowledge that many different types of behavior may explain insolvencies. Nonetheless, investors and supervisors alike must condition their decision making on available financial reporting. Seminal academic work such as [Altman \(1968\)](#) and [Shumway \(2001\)](#) precisely attempt to shed light on how simple financial ratios can be used by such parties. Applying this empirical approach to insurance, we seek to use historical data to help understand the following questions:

- While the years directly preceding an insurance impairment will see lower net income levels, do losses occur suddenly (through, i.e., a sudden spike in claims) or instead do they occur more gradually through time?
- What is the relative weight of macroeconomic determinants in insurance failures, as opposed to purely idiosyncratic, firm-level characteristics?
- While an increase in premiums by an insurer may be a sign of better performance, increasing market shares may also reveal underpricing or “gambling for resurrection” for a low profitability firm. Do failing firms experience a spike in premiums prior to collapse?
- What is the relationship between reinsurance ceded and the stability of equity/own funds? Without knowing detailed information about reinsurance treaties, do ceded premiums lower the volatility of net income relative to written premiums, or may it create reinsurance risk due to the complexity of the arrangements?
- Governance problems within insurance firms are often mentioned as a major source of insolvencies, and (as discussed below) various estimation techniques are used in the

literature to capture a firm’s operating inefficiency. Financial supervisors, however, typically concentrate on simple ratios. Can operating and administrative expenses capture a firm’s governance quality?

- How do insolvency determinants vary according to a country’s institutional or jurisdictional framework?

The remainder of the paper is organized as follows: Section 2 reviews the existing literature, section 4 presents the novel dataset and some summary statistics, and section 5 outlines our expected results. Section 6 details our econometric approaches and expected results. Section 7 reports our results and robustness checks, and 8 concludes.

2 Review of the Literature

The early insurance insolvency literature dealt mainly with the predictive performance of regulatory ratios and ratings. Ambrose and Seward (1988) use a multivariate linear discriminant analysis approach in which A.M. Best ratings are combined with information given by financial statements. The authors find significant predictive power in the premiums-to-surplus ratio, the loss ratio and time spent settling claims; the expense ratio, return on equity (or, in some jurisdictions, “surplus” for insurers) and return on assets were not significant predictors. Cummins et al. (1995) document the inadequacy of NAIC’s RBC ratios, finding predictive power “very low” without additional regressors. Cummins et al. (1999) later compare the accuracy of the next generation of indicators—NAIC’s so-called Financial Analysis and Surveillance Tracking (FAST) audit ratio system—with the classic risk-based capital (RBC) prudential measures. The authors find that while the “FAST” system dominates RBC ratios, predictive power remains low overall without additional inputs.

The more recent literature on insurance insolvency is related to four considerations: (i) efficient management and corporate governance, (ii) industrial organization, (iii) the macroeconomic environment, risk appetite and portfolio choices, and (iv) profitability. We review the literature in each area.

First, different measures of “efficiency” or management quality have been proposed by academic studies. Leadbetter and Dibra (2008) show that management quality and risk appetite have been responsible for Canadian property-casualty insolvencies, although the authors posit that an adverse macroeconomic environment is often what pushes a company over the edge. Leverty and Grace (2010) examine two methods for measuring output in property-liability insurer efficiency studies. The authors find that efficient “value-added approach” firms are less likely to go insolvent, while firms characterized as efficient by the

“flow” approach are generally more likely to fail. In a later study, [Leverty and Grace \(2012\)](#) find the managerial ability of CEOs to be inversely related to the amount of time a firm spends in distress, the likelihood of a firm’s failure and the cost of failure. [Zhang and Nielson \(2015\)](#) incorporate state-specific factors on a U.S. database of property-casualty failures, finding that insurers with low business-line diversification, fewer failed Insurance Regulatory Information System ratio tests and membership in a larger group are less likely to become insolvent. Most recently, [Eling and Jia \(2018\)](#) show how “technical efficiency” is associated with financial health across the entire European sector.

Second, market structure is shown to matter. The earlier literature focused on a possible tradeoff between competition and financial stability, arguing that less market concentration (increased competition) increased the occurrence of firm failure, particularly in the non-life industry. [Browne and Hoyt \(1995\)](#) find non-life insolvency to be significantly tied to low market concentration—more insurers lead to slimmer margins and more failures—and further estimate the industry-wide combined ratio to have predictive power for insolvency. [EIOPA \(2018\)](#) documents a similar trend: most detections of non-life insolvency are small firms with low market share, which, the authors point out, mirrors the structure of the EU insurance market. In contrast, the more recent literature, notably [Cummins et al. \(2017\)](#), shows how increased competition throughout the EU pushes firms towards greater efficiency, improving the financial health of the sector. [Zhang and Nielson \(2015\)](#) also argue that highly concentrated insurers exhibit higher insolvency risk. Studying the period 1994 to 2008, [Cheng and Weiss \(2012\)](#) show that insolvencies in the property-liability insurance industry are positively correlated to the industry-wide Herfindahl index of premiums written. This is consistent with Panzar-Rosse analysis (see [Shaffer and Spierdijk \(2015\)](#)) often used in banking which tends to show that, unlike competitive firms which are able to protect profits by increasing prices when costs are rising, less competitive markets respond more slowly, implying profits may be more sensitive to any shocks on costs that would magnify their inefficiencies, leading to an increase in insolvencies. We will later investigate to what extent insolvencies may be higher in more concentrated, hence less competitive, insurance markets.

Third, the health of insurance companies often fluctuates with the macroeconomic environment. The life insurance industry is widely understood to exhibit more interconnection with the macroeconomy, depending on the degree of liquidity of liabilities and the subsequent financial nature of the business. 37% of life insurers in EIOPA’s 17-year study experienced their failure or near-miss in the 2007-2008 window (see [EIOPA \(2018\)](#)). [Browne et al. \(1999\)](#) shows how life insurers are sensitive to long-term interest rates, personal income, unemployment, stock markets and also the number of insurers present in the industry. In addition to

firm size, [Chen and Wong \(2004\)](#) finds asset returns to be a high-ranking factor explaining insurance company distress in both life and non-life sectors of the Asian insurance market.

Unlike property-casualty insurance, however, life policyholders may be able to withdraw funds to invest elsewhere. [Kim \(2005\)](#) explains surrender as a function of several economic variables, finding that increases in the interest rate often lead to disintermediation.² Unemployment, GDP growth rates, seasonal effects and policy age appear important as well. [Cheng and Weiss \(2012\)](#) analyse the macroeconomic factors involved in non-life insolvency, ultimately reaffirming the relevance of interest rate changes and market concentration. [Russell et al. \(2013\)](#) also tests the sensitivity of life insurance surrender to macroeconomic variables, finding a positive correlation to interest rate levels and a negative relation with income levels and interest rate spreads.

Connected to that, several papers show that insurance portfolio choices matter. Existing literature stresses the role of changes in asset mix for defaulting undertakings, linked to attempt to escape from difficulties by reshuffling assets (see, e.g., [Carson and Hoyt \(1995\)](#)). However, investment structure also plays a role—in particular, investing in less volatile assets such as sovereign or corporate bonds is likely to reduce the risk of insolvency. This is in line with insurance regulation designed to protect insurance policyholders. [Lee and Urrutia \(1996\)](#) find that the ratio of market value of invested bonds to total admitted assets is a significant variable to predict non-life insurance insolvency in 1980-1991. Similarly, using P/C insurers' insolvency data from 1998 to 2008, [Zhang and Nielson \(2015\)](#) document that the share of assets invested in bonds is significantly lower for firms which eventually experience insolvency.

Fourth and finally, the link between profitability and failure has been addressed by several authors in the literature. [Eling and Jia \(2018\)](#) show how, while ROE is weakly associated with health, its volatility positively correlates with the probability of failure. [Bernard et al. \(2016\)](#) use internal firm-level data from the French Prudential Supervision Authority to derive leading indicators of insurance distress. Although the econometric analysis yields few significant results, low levels of reserves and weak profitability appear to precede financial vulnerability.

3 Jurisdictional and Institutional Heterogeneity

The database allows us to investigate to what extent insurance company insolvencies may have different determinants across countries. Several factors can help explain this phe-

²Interestingly, in recent years, policyholders' sensitivity to the interest rate has seemed to diminish, implying substantial inertia in savers' behavior.

nomenon: the legal environment regarding insolvency, supervisory activism, market structure, and finally differences in contract-level guarantees.

Regarding the first dimension, insolvency regulations may differ across countries, and especially in the insurance industry as many such companies often receive a special treatment because of the sector’s regulated status and the importance of insurance to the rest of the economy. Firstly, insolvency procedures can include out of court arrangements, which often remain confidential but are common in the UK and in the US. Secondly, they may involve proceedings under the supervision of courts, including so-called rehabilitation (notably in the US and Japan, as well as administration in the UK, and so-called “redressement judiciaire” in France). Finally, a firm can enter liquidation. Court decisions across countries may strike a different balance between the different stakeholders, however: while the UK is more creditor friendly, France and Japan are debtor friendly, with the US somewhere in the middle (see [Asai \(2021\)](#), [Simon Beale \(2021\)](#), [Joanna Gumpelson \(2021\)](#), and [Alan Kornberg \(2021\)](#)). This is also consistent with the view that some countries like the UK or the US might be less reluctant to allow insurance firms to fail than in continental Europe and Japan (see [Eling and Jia \(2018\)](#) for the EU).

Regarding the second dimension, continental European countries often experience more prudential activism from public authorities, which attempt to alleviate market pressures, while the UK has a more market oriented approach which is more protective of policyholders. Overall, such factors may be indistinguishable from the previous dimension discussed above. Ultimately, the hypothesis to test for both cases is therefore whether economic determinants may have more explanatory power to predict insolvencies in US and UK than in France and Japan. In the empirical analysis, we test the role of shocks on firms’ profits to predict insolvencies. Note, however, a possible caveat, in the sense that market-oriented countries may undergo more out-of-court settlements, so that the insolvencies defined by court proceedings or regulatory intervention may result from market failures. A detailed analysis of asset transfers by insurers close to insolvency would overcome this issue, but is beyond the scope of the current article. Nevertheless, a first hypothesis to test is the following:

- **Hypothesis 1:** ROA provides a better signal of insolvencies in more market-oriented countries

The third insolvency dimension mentioned above—market structure—may also imply differences in terms of response of insolvencies. Specifically, the different countries under study exhibit clear difference in terms of market concentration. As shown in [Figure 1.16](#), the Herfindal-Hirschman Index is bigger in France than elsewhere, providing evidence of a

less competitive environment. This figure reflects the distribution of gross premiums across a given country's market in a given year. As discussed above, in line with the analysis conducted in [Shaffer and Spierdijk \(2015\)](#), we test the hypothesis that a shock on an insurance firm's costs has a larger effect on insolvencies in less competitive environments (namely, in France or Japan, versus in the US).

- **Hypothesis 2:** Shocks to operational inefficiency matter more for insolvencies in countries where insurance markets are less competitive

The last dimension addressed above is product differentiation. While investing in less volatile assets like bonds is likely to reduce P/C insolvencies ([Lee and Urrutia \(1996\)](#), [Zhang and Nielson \(2015\)](#)) the question explored here is whether it may hold for life insurance as well and similarly across national jurisdictions. Indeed, using OECD data, [Gründl et al. \(2017\)](#) show that countries differ markedly: the share of insurance assets invested in bonds is lower in Asia than in Europe and US. In addition, insurers may invest in risky bonds, while offering generous guarantees on yields to policyholders as in Japan, which ultimately turned detrimental to financial stability with the failure of many life insurance companies in the late 1990s and early 2000s. This leads us to test the following hypothesis and investigate possible differences across countries:

- **Hypothesis 3:** Bond portfolio investments offer protection to insurance companies

Note that due to data constraints, we compare France and the United Kingdom with the US in our analysis of the non-life sector, and Japan to the US in our analysis of the life sector. As discussed below, our results allow us to reject Hypothesis 1. Indeed, ROA exhibits a stronger effect in the US than France and Japan, but the effect is not statistically significant. Hypothesis 2 is verified for non life insurance in France, while Hypothesis 3 is verified in all countries, with the important exception of Japan.

4 Data

After explaining how the data were assembled to create a new international database on insurance impairments, we provide a few summary statistics.

4.1 Constructing an International Database of Impairments

To build an international database on impairments, we extend to other countries of similar level of financial development (France, Japan and the UK) the approach followed in

the insurance insolvency literature in the US (especially on P/C insurance), which typically measures insolvency at the date of public intervention. Such a procedure ranges from action taken by courts, to intervention from the regulator as it triggers the suspension of new business, to the most severe case dimension being the liquidation of the insurance company.³ BarNiv and McDonald (1992) on P/C insurance, for instance, define insolvency including liquidation, receivership, conservatorship, restraining orders and rehabilitation. The authors note that all mergers or acquisitions of insurers which cause disappearance of the companies should not be regarded as distress or insolvency. Cummins et al. (1999) measure insurance insolvency in the non-life industry by the first public regulatory order involving a company. Any formal state regulatory order including restrictions on management, conservation, rehabilitation, or liquidation was treated as a failure. These US failures were reported to the National Association of Insurance Commissioners (NAIC). Leverty and Grace (2012) define insolvent insurers as those affected by a formal regulatory action in the form of proceedings for conservation of assets, rehabilitation, receivership, or liquidation. Zhang and Nielson (2015) use A.M. Best's definition of insolvency: a company is financially impaired when the first official action is taken by the insurance department in its state of domicile, whereby the insurer can no longer conduct normal insurance operations. State actions include supervision, rehabilitation, liquidation, receivership, conservatorship, cease-and-desist order, suspension, license revocation, administrative order, or any other action that restricts a company's freedom to conduct business normally. For Eling and Jia (2018), failure events include ceased operations, in liquidation or liquidated, in runoff, portfolio transfer, inactive, and insolvent insurance firms. However, M&As were excluded

The data for this study has been gathered from several sources, including guaranty fund associations,⁴ the National Association of Insurance Commissioners, the UK Prudential Regulation Authority (PRA), internal French Prudential Supervision Authority (ACPR) data, AM Best and Bloomberg. The failure events or, as we term them, "impairments" are strictly defined as either a regulatory intervention of a local supervisor (leading to the suspension of the insurance licence, which may only be temporary with a subsequent recovery) or the start of court proceeding in the form of rehabilitation or liquidation. With rare exceptions, these actions prevent firms in question from underwriting new business. The only jurisdiction in which firms could be allowed to underwrite new business following a supervisory intervention

³In many cases, the start of court proceedings allows the regulator to withdraw the license to underwrite business. For instance, in France, liquidation is possible either after the withdrawal of the license by the supervisor (liquidation is automatic for insurance companies but not for reinsurance companies), or in case of suspension of payments. For other types of procedures, the supervisor is informed and a mutual agreement is sometimes required.

⁴Examples include the National Organization of Life and Health Insurance Guaranty Associations (NOLGHA), Property and Casualty Insurance Compensation Corporation (PACICC), Assuris and Protektor.

is the United States. Of the 1,465 firms which entered receivership through 2016, only 9 were recorded as being authorized to write or rewrite new business. Simple profit warnings or supervisory audits without actions limiting activity are not considered as impairments, nor are firms who enter run-off without knowing the motivation for this status. Lastly, M&As are excluded, as well as portfolio transfers, as we concentrate on cases where markets or supervisory authorities failed or did not intend to intervene ex-ante.

Moreover, there are different ways to define an insurance company failure from an economic point of view. The scope of financial troubles leading to a failure could range from market warnings, substantial losses, partial suspension of activities or withdrawal of agreement by the supervisor, with liquidation being the most extreme consequence. It is important to note that, as we have defined an impairment, some impaired firms in our database may eventually return to financial health, although in practice few do, and those who survive only do so thanks to a major restructuring or large-scale government bailout. We consider this definition helpful from a supervisory point of view, as it allows us to predict (and thus, hopefully, help prevent) any case that was destabilizing enough to prompt intervention, as opposed to just those cases which fit a specific legal definition (which may change across jurisdictions). Indeed, only considering liquidating firms would ignore cases of firms which were acquired following a supervisory intervention.

Following collection from the sources mentioned above purely regarding the impairments, our database contained 1,607 cases across life and non-life sectors. We include all major insolvencies described in [Michelle Brennan \(2013\)](#) or [Baranoff \(2015\)](#) as well as many others. These company-events are matched with available historical financial data for these companies. The latter data (principally, SNL datasets, described below) are also used to define a control sample of companies. Our study focuses on solo undertakings, excluding groups to the greatest extent possible. Such information was not always provided by our sources, requiring manual cross-checking. A main motivation to exclude groups was to isolate failing firms from a conglomerate, which can often fail either due to one unhealthy firm, or due to non-insurance related financial troubles. We were therefore especially careful to exclude the parent company of any individual firm in our sample.

In order to be as comprehensive as possible, we used standard sources for historical financial data. This includes SNL Market Intelligence, the Prudential Regulation Authority (Bank of England) for UK cases, the Financial Services Agency for Japanese cases and the French Prudential Supervision and Resolution Authority for French cases. We do not, however, have historical balance sheet and income statement data for all of the 1,000+ identified cases of impairments. Taking the intersection of these impairments with the available series of historical financial data, we were left with 495 “impairments” out of 8,893 total companies

in our database. An additional data-treatment step consisted of determining the *de facto* date of failure for cases in which failure year provided by our sources surpassed the last available year of financial data. In such limited number of cases, we associated the failure event with the last available firm-year data observation. We further note that the available data led us to concentrate on firms' risk management leading up to a failure, without addressing the issue of final dividend payouts to policyholders after, for example, a liquidation.

Finally, we cleaned the database of abnormal values, notably by dropping companies below \$1 million in total assets and trimming values outside of the 1.5 and 98.5 percentiles, similar to [Eling and Jia \(2018\)](#) and [Cummins et al. \(1995\)](#), to correct for noise in our data which yielded economically implausible values in key ratios. The dataset remains quite extensive with well over 50,000 (company-year) observations. Our final database contains 287 property and casualty (PC) impairments and 150 life and health (LH) failures, totaling 437 across both, although we note that the number of impairment cases (i.e. impaired companies) included in most regressions (notably our baseline regression) is 263 (183 PC and 80 LH). This loss of cases in our estimates is due a lack of correspondence between the available financial data of a firm in SNL and the year of its failure. To our knowledge, this figure remains the largest unique dataset of its type for large countries in an academic study with a global perspective.

Macroeconomic data on 10-year government bond yields and the output gap were taken from the OECD Economic Outlook database. [Figures 1.1 and 1.2](#) show how the output gap and long-term interest rates have evolved through time in the countries in our sample. We adopt the output gap as a continuous measure of the macroeconomic cycle, while we use the long-term interest rate due to its linkages with the typical insurer's balance sheet.

4.2 Summary Statistics, Impaired vs. Healthy

Below, we report a few summary statistics regarding companies which at some point become impaired, as compared to the control group of companies who remain healthy in our database.

As shown in [Tables 1.1 through 1.3](#), financial ratios for impaired companies are on average quite different from those of healthy companies. [Table 1.3](#) shows such t-tests broken down by firm type (implying separate tables for non-life and life insurers). Data on total assets has been converted in USD in [Table 1.1](#), while the data used for the ratios in [Table 1.2](#) have been left in reported currency. A few striking conclusions can be drawn from these t-tests.

First, [Table 1.1](#) shows that failing companies generally tend to be smaller across all four countries, a stylized fact also shown in [EIOPA \(2018\)](#). We also confirm from our database

the intuition that performance, as measured by ROA and ROE, is lower for firms which eventually fail. The latter group of companies exhibits more dispersion across all insurers in our study. Further, these performance measures are much less stable amongst firms that fail; indeed, the volatility of ROE is over twice as big for failing firms, even after trimming outliers as previously described.

Averaging over all periods, firms which fail appear to invest less in fixed income investments such as bonds, and slightly more in real estate. We also see that failing firms spend greater amounts in operating and administrative expenses, expressed as a share of written premiums.

While we have collected impairments as far back as 1975, the bulk of our balance sheet data for US firms begins in 1996 (our UK, Japanese and French data begin in 1986, 1987 and 1992, respectively). We choose to only report in these histograms cases for which we have available financial data, and therefore which will be included (depending on the specification) in our regression results. We report histograms for the failures by distinguishing between US and non-US cases in Figures 1.3 and 1.4.

Figure 1.5 provides evidence of the cyclical nature of impairments, with spikes in the US in the mid 1980, in the early 1990 associated with Hurricane Andrew, and in 2001 following the September 11th attacks (see [Cheng and Weiss \(2012\)](#) for more on the role of hurricane exposure in the non-life industry). Many studies, as mentioned above, also relate these waves with the increasing entry into the sector at the time. There are also spikes in impairments around the 2007 Financial Crisis for US and non-US cases (as in [EIOPA \(2018\)](#), for the latter, using a more restricted dataset).

5 Expected Results

In order to explain insurance failures, we refer to “insurance ruin theory”, as explained by [Plantin and Rochet \(2007\)](#), which leads to imposing capital requirements to ensure that equity E is such that

$$E \geq 2\sqrt{A_1^2\sigma_r^2 + R^2\sigma_x^2}$$

where A_1 is the risky asset in which the insurer invests the premiums collected, σ_r^2 is the standard deviation of the return on the risky assets held by the insurer, R the amount of reserves or technical provisions and σ_x^2 , the standard deviation on the unit cost for the insurer (as percentage of reserves, which measure to what extent initial reserves may diverge from the ex-ante assessment). The insurer defaults if this condition is not met. Such an equation assumes independence between technical and financial risk. In addition, extending

to different risks, as well as diversification across risks leads to a formula close to the US Risk Based Capital or the Solvency II definition of the Solvency Capital Required. In such a formula, defaults occur when equity is too low, if assets face capital losses in case of a sudden increase in interest rates, or if reserves are not properly assessed.

According to another approach, where a portfolio of N risks is introduced (see also [Plantin and Rochet \(2007\)](#)), the insurer fails if $E + N(1 + \rho) \leq (\tilde{S}_1 + \tilde{S}_2 + \dots + \tilde{S}_N)$, where ρ are the premiums collected on each of the N risks (they are assumed to be similar, without loss of generality, with mean normalized to one and standard deviation of σ). Using Chebyshev's inequality, this leads to:

$$Pr(default) \leq \frac{N\sigma^2}{(E + N\rho)^2}$$

Defaults can therefore be avoided by increasing equity E , or N the number of risks, or tariffs ρ , or by decreasing σ through, e.g., reinsurance. However, such a formula does not take into account the risks associated with an uncontrolled increase in the size of the portfolio. Furthermore, moral hazard or adverse selection needs to be taken into account, in order to ensure that shareholders and managers implement the appropriate internal risk control, and do not “gamble for resurrection” if they do not have enough “skin in the game”, or if their stakes decrease over time.

In our database, $Impairment_{jit}$ stands for an impairment of company j , in country i at time t . The determinants of impairments are individual financial indicators (balance sheet, P&L, etc) as well as macroeconomic variables (interest rates, output gap, as indicated above). Regarding financial variables, we use:

- Return on assets (Net income/Total assets),
- Return on equity (Net income/Total equity),
- Total assets (in log),
- Share of fixed-income instruments in total investments,
- Loss ratio (Claims/Gross Premiums),
- Portion of gross premiums ceded to reinsurers,
- Operating inefficiency (Operating expenses/Gross premiums), labelled as $OpExp$,
- Growth rate in gross written premiums,

The values used for the log of total assets (to control for size) have been converted to USD. Since all other variables are ratios, values have been left in reported currency. Note that we have chosen to use gross premiums so as to avoid a bias in the ratio (used to capture the size of the flow of business in a year) due to the choice of a firm to cede risks to a third

party.⁵

Below, we map the expected sign for each parameter estimated in our baseline empirical analysis.

⁵Ambrose and Seward (1988) use (acquisition expenses + administrative expenses)/Gross premiums; Chen and Wong (2004) use a similar ratio.

<i>Variable</i>	<i>Impact on impairments</i>	<i>Hypotheses</i>
ROA	(–)	Insurers running losses are more likely to become insolvent.
Size	(–)	Bigger firms (measured by the log of total assets) can better absorb shocks, and the law of large numbers should result in lower underwriting risk for larger firms.
Capital/Reserves	(–)	Firms with higher risk-based capital have a low failure rate.
DebtIns	(–)	Fixed-income assets are often held to maturity by insurers, and are generally considered less risky.
LossRatio	(+)	Higher loss ratios erode PC insurers' bottom lines and own funds; higher values indicate lower financial health.
Reins	(–)	Depending on the reinsurance treaty, ceding premiums to a reinsurer can serve to transfer risk, lowering an insurer's exposure.
OpExp	(+)	Cost-inefficient firms mismanage their resources and perhaps engage in risky behavior to attempt to remain competitive.
PremGrowth	(–/+)	(+) For longer lags, fast growing companies can lack underwriting prudence, and collect such volume precisely due to underpricing risks. An endangered firm may grow their business in order to gamble for resurrection. (–) On the other hand, in the short run, disreputable firms may struggle to collect premiums (e.g., following an A.M. Best downgrade), or may face surrenders, accelerating a failure.
IntRate	(–/+)	(–) level has a negative effect on failures: higher interest rate levels provide higher returns for long-term bonds popular among insurers; (+) changes or upward movements may lead to disintermediation for certain life insurance contracts, as policyholders surrender to exploit higher interest rates available elsewhere.
OutputGap	(–)	To the extent that insurance risks (or the market risk borne in their investments) are correlated with recessions, macroeconomic crises pose a threat to insurers; in addition, personal financial distress associated with higher unemployment may lead policy holders to surrender.

6 Econometric Approaches

The empirical analysis is based on logistic regressions where we explain the likelihood of default events using a set of economic and financial determinants. We additionally estimate duration models in which the explanatory variables (depending on parametric definition) either help extend or serve to reduce a company’s survival time in the sample. As logistic and duration models are very close, the second one may be viewed as a robustness check of the former; see Allison (1984) for a review of survival analysis.

6.1 Fixed Effect Logistic Regression

In logistic regression, we assume the probability of an impairment can be written as follows:

$$\ln\left(\frac{p_{i,j,t}}{1 - p_{i,j,t}}\right) = \beta_{i,t}\gamma_{i,t-k} + \delta_{i,t}\theta_{i,j,t-k} + \alpha_i + \alpha_t + \epsilon_{i,j,t-k} \quad (1.1)$$

where the log-odds of becoming impaired at date t become a linear function of our explanatory variables (with $k \geq 1$).

$\gamma_{i,t}$ represents a vector of macroeconomic factors for country i , namely the long-term interest rate and the OECD output gap. α_i is the country fixed-effect for country i , while α_t is the time fixed effect for year t . $\theta_{i,j,t}$ represents a vector of individual financial variables.

Further, we estimate predictive margins to evaluate our logit results in a more intuitive fashion. Instead of a covariate’s effect on the log odds, this transformation gives us:

$$\frac{\partial Pr(\text{Impairment} = 1 | X_1 = x)}{\partial X_1} = \frac{\Delta P}{\Delta X_1}$$

or, the effect on the predicted probability following a discrete change in an explanatory variable, X_1 .

This can be done in a number of ways. The approach we adopt is to plot incremental jumps (e.g., 2.5pp jumps in ROA, from -10% to +10%) in a given variable, and calculate marginal effects using different “predictive margins” for each of these values. Computationally, this consists of calculating a predicted probability of failure (\hat{p}) for each observation after universally replacing ROA by the given value, while leaving the rest of the observed values for other variables unchanged⁶ By differencing these predictive margins obtained at two different given ROA values, we are able to understand the impact on the probability of failure due to a discrete change in this variable, keeping other variables at their observed

⁶This is known as “average marginal effects.” Values for \hat{p} are then averaged across all observations, and a “predictive margin” for this ROA value is yielded.

values. For reference, we have additionally included such marginal effects where other covariates have been held at their *mean* values, which in practice does not severely impact our values.

6.2 Survival Analysis

To proceed with the parametric estimation of a survival model, we first assume survival time T to follow a certain distribution:

$$S(t) = P(T > t) = \int_t^{\infty} f(u)du$$

The baseline distribution $f(t)$ in our estimations will be the Weibull distribution (although we test others as robustness checks):

$$f(t) = \lambda pt^{p-1} \exp(-\lambda t^p)$$

This will yield, respectively, the following survival function:

$$S(t) = \exp(-\lambda t^p)$$

and the hazard function ($h(t) = \frac{-dS(t)}{dt}$) becomes in that particular case:

$$h(t) = \lambda pt^{p-1}$$

If $p = 1$, the model becomes the exponential function with constant risk over time. $p > 1$ means risk increases over time, while it decreases through time with $p < 1$.

There exist two families of such so-called parametric survival models: proportional hazards (PH) models and Accelerated Failure Time (AFT) models. In PH models, the covariates are assumed to have a multiplicative effect on the hazard function. PH regression thus estimates the effect of $\exp(-x_j\beta)$ on the “hazard ratio”, either accelerating or decelerating (\leq 1) time to failure for each insurer:

$$h_i(t) = \lambda pt^{p-1} \exp(\beta' \mathbf{x}_j) \tag{1.2}$$

where x_j is a vector of covariates, β is a vector of regression coefficients.

In the AFT framework, the dependent variable is the (log of) the survival time:

$$\log t_j = \mathbf{x}_j \beta + z_j \tag{1.3}$$

where z_j is the error term with a specified density. A one unit increase in the covariates decelerate or accelerate the time to failure.

In our setup, we measure survival time as the number of one-year periods a firm has survived relative to its origin—assumed to be the year in which its historical data series begins. At each period, a firm will either experience a failure (in which case its terminal survival time becomes known), or it will be considered “censored”, meaning that the observation window ended before the individual experienced the event. This type of data is referred to as “right-censored.” The likelihood function to be estimated for such data is written as follows:

$$L = \prod_{i=1}^N [f(T_i)]^{C_i} [S(T_i)]^{1-C_i}$$

Non-censored observations thus contribute directly to the chosen density $f(T_i)$, while censored observations intervene in the survival function $S(T_i)$, contributing the information that a firm’s terminal survival time T_i is at least later than the current measurement period t . In this way, all information from both impaired and never-impaired firms are taken into account in the estimation procedure.

For parametric estimations of proportional hazards models, one typically reports hazard ratios instead of traditional coefficients; if the hazard ratio for a predictor is close to 1, then its effect is null. Hazard ratios are below one for variables which are “protective” or “healthy” (extend life), while values above are associated with increased risk. As with a logistic regression, all of the parameters are estimated taking the other predictors into account. Instead of hazard ratios, we here directly report traditional parameter estimates, which represent the increase in the expected relative hazard for each one unit increase in the predictor, holding other predictors constant. Positive coefficients therefore are associated with shorter survival in the sample, and vice versa.

Note that in the Accelerated Failure Time (AFT) specifications, the interpretation of coefficients changes considerably, since the dependent variable is no longer the hazard rate but the survival time. With this approach, positive coefficients *delay* failure (as opposed to increasing the hazard rate under the PH metric), while negative ones accelerate failure. It should also be emphasized that such estimates can accelerate or decelerate time to failure without necessarily affecting the hazard rate, which can yield certain intuitive advantages to the approach depending on the specification.

7 Results

For our baseline logistic regression specifications, we include a single (interacted) country-year fixed effect, similar to Eling and Jia (2018), to account for the macroeconomic context and other jurisdiction-specific characteristics of a given country. Firm-level fixed effects could not be used for this type of analysis as it would drop the entirety of our control sample (i.e., those firms which never experience a failure since there is no variation to be explained in y_{it} (meaning $Pr(Default)$)). We later explicitly include macroeconomic variables (the output gap and the interest rate) as robustness checks, and further show specifications using separate time and country fixed effects.

Our analysis is split across the two sectors owing to their innate differences: Tables 1.4 and 1.6 report our results for the non-life sector, while Tables 1.7 and 1.9 report our life sector results. Separating the two sectors allows us to provide various contributions to the academic literature. We later discuss the ways in which these determinants vary across national jurisdictions.

7.1 Non-life sector

In this section, we will discuss our results that pertain only to the non-life sector, found in Tables 1.4 and 1.6.

We first note that profitability, measured by ROA—used widely in the literature as a measure of firm performance—, is strongly significant across all columns, as is ROE, for both approaches (logit or survival). At the margin, we find that a one standard deviation increase in ROA decreases the probability of default by 0.28 percentage points in absolute terms, or 0.23pp when holding other covariates at their means. Zhang and Nielson (2015) also use ROE as measure of profitability, similarly finding that higher levels help prevent failure, as the literature suggests for ROA. Higher loss ratios appear to weakly decrease survival (for a given level of ROA), implying that claims management and proper pricing help for the continuation of insurance firms. The significance of the loss ratio confirms the findings of Ambrose and Seward (1988) while again challenging Lee and Urrutia (1996) with a much more complete and current dataset.

We also note that the coefficient for operating inefficiency is positive and significant across all specifications. This result confirms Zhang and Nielson (2015), who find a significantly higher expense ratio on a sample including 98 insolvent property and casualty firms, and Leverty and Grace (2012) who show how managers can be responsible for running inefficient (and thus more failure-prone) firms. Our result remains novel given the breadth of our data and the choice of variable to instrument for operating inefficiency (*OpExp* variable

in the tables). While our ratio (administrative and operating costs over premiums) is less complex than other techniques found in the literature (such as the Data Envelope Analysis approach in, for instance, Cummins et al. (2010)), our approach is of increased practical interest to supervisors, who typically evaluate simple ratios to gauge the health of undertakings. Evaluated at the margin across all observed values, we find that a one standard deviation increase in our operating inefficiency measure (i.e., 23 percentage points (pp.)) increases the probability of default by 0.15 pp. As shown in Figures 1.8 and 1.9, this absolute increase in $Pr(Default)$ should be understood as a deviation from the unconditional firm-year probability of default of 0.5pp. Relative to this baseline probability, such a movement increases the probability of failure by 30%. When holding other covariates at their sample mean values, this amount drops slightly to 0.11pp.

Looking to the asset side, we see that the share of debt instruments in a firm's investment portfolio, controlling by the other explanatory variables, is far outside of statistical significance in the property and casualty sector, directly challenging Lee and Urrutia (1996). Overall this result underscores the relative importance of the liability side of the balance sheet in this sector; due to the faster production cycle and shorter liability duration, a firm's efficiency (in settling claims, for example) is of paramount importance for its survival. After splitting this sector off from the life sector, portfolio choice does not appear to play a significant role in predicting failure.

Perhaps unsurprisingly, after inclusion of our country and time fixed effects, our macroeconomic variables lose all significance: the long term interest rate is the only significant variable (see column (3) as compared to column (4)). In our estimates, we find weak evidence of *higher* levels of ceded premiums to reinsurance being associated with a higher probability failure in the non-life sector. This is in line with Leadbetter and Dibra (2008) which show reinsurance to be a contributing factor to insurance insolvency for 26 percent of the insolvencies in Canada during the 1960–2005 period. Two explanations are provided by the authors: complex inter-group arrangements, and over-reliance on reinsurance assets that became more difficult to renew at some occasions. In our case, we interpret this as a self-selection effect, whereby less healthy insurers observe their risk levels, and attempt to share more of this risk with a third party. Our t-tests confirm a well-documented fact that reinsurance is more popular in the property-casualty sector than in the life sector. Finally, we find that a lower loss ratio (claims/premiums) helps survival.

We also note that size matters for almost all our specifications, with a negative sign. This captures the fact, *ceteris paribus*, smaller firms tend to have a less diversified portfolio of activities and are more likely to fail in comparison to larger undertakings.

Finally, our parametric survival model results are largely in line with our logit results:

operating inefficiency significantly predicts failure, asset mix is not important and strong firm performance (ROA, ROE and loss ratio) intuitively prevents insolvency.

Cross Country: France & UK vs US

As discussed above, differences across countries may be associated with supervisory activism that may pay more attention to certain specific indicators, or differences in market structure. In the second case, more competitive markets imply that any shock on costs is immediately passed on to policyholders via pricing, keeping margins constant. Conversely, in a market with monopoly power, firms do not adjust prices in response to shocks but instead reduce their margin—and as a consequence, such cost shocks may be more destabilizing.

As seen in Table 1.5, where we interact the ROA variable with country dummies (for France and UK), the role of profitability does not appear to vary across jurisdictions, as the country interaction terms are not significant (implying the absence of differences across countries). However, repeating the same experiment for operating inefficiency, by adding country dummies interacted with that variable, we find a significant and positive coefficient for France (6.37), which should be added to the baseline effect on the log-odds (1.31); the coefficient is positive as well for the UK (2.13) but outside of statistical significance. Overall, we can conclude that operational inefficiency matters most in the French case, and (to a lesser extent) in the UK. These results are consistent with Figure 1.16: less competitive insurance markets with lower resistance to shocks appear to be more vulnerable. When firms *do* fail in such jurisdictions, management problems can be laid bare, as suggested here by our results. Note, moreover, that this may also reveal more activist supervision as regulators intervene more strongly to shocks to operating costs.

7.2 Life sector

As previously stated, by dividing the two sectors, we are able to emphasize their inherent differences. Our baseline life sector results can be found in Tables 1.7 and 1.9. In the life sector, we see that our firm profitability measures play a lesser role; ROA is more weakly significant in Tables 1.7 and 1.9. At the margin, a one standard deviation increase in ROA decreases the firm-year probability of default by 0.24 percentage points (0.18 with other covariates at their means, see Figure 1.12), compared with 0.28pp in the non-life sector. One explanation for this small contrast with the non-life sector is the fact that profits and losses in the life insurance sector can be smoothed out over several years,⁷ implying less

⁷In France, the *Provision pour participation aux bénéfices* allows insurers to distribute investment profits to policyholders up to eight years after their realization.

importance for the profitability of one given year. Non-life firms, however, have no such smoothing mechanism helping them to remain competitive in bad times. The duration of the liability side is typically much lower in this sector, as well, regardless of jurisdiction. Lastly, reinsurance appears to play no role in firm survival for life companies.

The most striking difference from the non-life sector is the importance of asset mix: the higher the share of debt instruments in total investments, the lower the probability of failure. This confirms our prior intuition that the asset side—and subsequent exposure to financial cycles—plays a larger role for life insurers. At the margin, a one standard deviation increase in the share of debt instruments in a life insurer’s portfolio (i.e., 24 pp) decreases the probability of failure by approximately 0.23 pp (virtually unchanged when holding other covariates at the mean, see Figure 1.13). Operating inefficiency appears to play no role, in stark contrast to the results for the property and casualty sector.

Overall, we broadly understand these differences to imply a heavier relative importance of market risk in the life industry, compared to the relatively larger factors of underwriting risk and efficient claims management in non-life. This result confirms that life insurance—a sector with a longer liability-side duration—is ultimately more exposed to macroeconomic conditions, while providing a simple intuition that has not directly been addressed in the literature; Cheng and Weiss (2012) explore bond portfolio duration, but not fixed-income instruments as a portion of the total asset mix. This is also purely a study of non-life insurers, and thus unable to highlight this marked difference regarding insolvency across these different business lines. Finally, as for the non-life sector, most of our country-year fixed effects are significant (particularly in crisis years), reflecting the importance of country-specific macroeconomic conditions across all sectors.

As a means of model selection, we report the Akaike Information Criterion (AIC) as well as Receiver Operating Characteristic (ROC) curves. The ROC curves tell us, for a given level of sensitivity (or, rate of true positives) what rate of false positives (1-specificity) we must tolerate. For example, in the property-casualty logit with contemporaneous lags, a threshold of our indicator (the \hat{p} of our estimation) which catches almost 90% of true insolvencies must come at the expense of a false alarm almost 25% of the time. While this underlines the difficulty of insolvency prediction, our Area Under the Curve (AUC) is in line with, although slightly higher than, the current literature (0.87, against 0.86 in Eling and Jia (2018)).

The AUC in ROC analysis serves as a measure of how good our estimated model is at discriminating between failures and non-failures. An AUC of 0.5 represents a model which is no better than a random guess, while an AUC of 1 corresponds to a flawless predictor. Including both the cases of false positives and false negatives (Type I and Type II errors), an AUC

of 0.87 corresponds to a model which yields an 87 % chance of successfully distinguishing between impaired and non-impaired firms.

Cross Country: Japan vs US

In this subsection, we compare the case of Japan (for which we have more exhaustive data for life insurance) to the US case. As seen in Table 1.8, we again notice no different role of profitability, in line with the non-life sector results. However, the effect of portfolio composition deteriorates in the Japanese jurisdiction, as evidenced by the statistically significant (positive) dummy variable. Baranoff (2015) points to the role of high interest-bearing guarantees on life insurance contracts which were, in this case, linked to market rates. Bernard et al. (2014) also stress that, in the years preceding the wave of Japanese insurance failures, guarantees offered by these institutions were greater than government bond yields. Arguably, such a result should be investigated further, as it may depend on the macroeconomic environment (in particular, whether interest rates are decreasing—leading to capital gains on bonds, provided bonds are measured at market value—or increasing).

7.3 Further Analysis and Robustness Checks

We have included three additional tables as a means to both explore additional dimensions and reaffirm the robustness of our previous results. We first provide, in Tables 1.10 and 1.11, additional lags for our explanatory variables. While this serves as a robustness check, it also helps us understand the timeline of a failure and gives an idea of the predictive power of these ratios through time.

Indeed, Figures 1.10 and 1.11 visually demonstrate the significance of these key variables through additional lags in non-life insurance. In this sector, a profitability shock significantly increases the probability of failure as many as three years in advance, indicating a notable sensitivity to profitability shocks which may prove hard to correct. The coefficient for operating inefficiency only gains significance in the second year leading up to a failure, suggesting that managers can perceive and correct for inefficiencies before they prove fatal. In other words, a firm's profitability three years ago matters for their financial health, while misdeeds related to management are not necessary impactful in a permanent manner.

Similar analysis is conducted in the life sector. Additional lags plotted in Figures 1.14 and 1.15 exhibit a contrast with those of the non-life sector. Here, ROA is only meaningful at the first lag; the second and third lags are firmly outside of statistical significance. The stronger leading indicator in this sector is the portfolio composition variable, which retains significance up to three years prior. We interpret this as a confirmation that profits and losses

are more easily smoothed in the life insurance industry due to its longer liability duration, lessening the importance of past ROA shocks.

Indeed, these results also outline the long-term nature of life insurance; indeed, a life insurance firm, with liability duration of ten or more years, may survive a profitability shock so long as their investment income does not falter. Non-life insurers, however, may struggle to recover from a bad surprise to the liability side, given the quicker speed at which they must settle their claims and inability to smooth losses through time.

Next, in Table 1.12, we test various alternative specifications. Given the relatively strong presence of smaller firms in our database, we tested whether our results could be driven by these small, somewhat idiosyncratic players (e.g., mutual insurers) whose broader pertinence could be questioned. By excluding firms below \$10 and \$20 million thresholds (see column 2-3 for non-life insurance, and 5 for life insurance), the previous results are unchanged, so that we can conclude that the results displayed in Tables 1.4 through 1.9 are robust to size. Further, given that we work mainly with ratios relative to levels of premiums, one may worry that our results are driven by a large drop or hike in the denominator of these ratios. By controlling for premium growth, our key ratios (operating inefficiency in non-life, and debt instruments in life) remain significant.

Finally, we carry out several additional checks in Table 1.13. In this table, we carry out the same analysis shown in Tables 1.4 and 1.7 but in the form of a single pooled regression. The interaction term in column 5 confirms our central life-sector result—(i.e., that portfolio composition matters for this sector but not non-life)—while our result with respect to operating inefficiency holds in column 6, albeit at the 10% significance level. ROA remains significant in the presence of these interaction dummies in the pooled regression. Further, we have created a distinct profitability variable that we introduce into several of each specifications. As mentioned previously, most of the insurance default prediction literature evaluates the role of profitability (e.g., via ROA or ROE) as well as operating inefficiency. However, unprofitable firms may struggle to bring in premium revenue, which may lead to capturing the same financial fragility through two different variables (see notably Eling and Jia (2018)). We therefore orthogonalize ROA with respect to operating inefficiency, by simply regressing ROA on operating inefficiency and introducing the residual as a new (orthogonalized) ROA variable (displayed in tables below as ROA^*). When using this variable, we observe that the $OpExp$ variable gains in significance and magnitude while other coefficients naturally remain unchanged. Additionally, we carried out this same analysis (ROA^*_{t-1} instead of ROA_{t-1} for the regressions in Tables 1.5 and 1.8. This does not change the significance of our results.⁸

⁸These results are available upon request.

8 Conclusion

In this article, we present evidence of the intrinsic differences between the life and non-life insurance sectors using a unique dataset of so-called “impairments” manually assembled by the authors. Applying logistic regression and parametric survival analysis to a dataset containing 150 life failures and 287 property and casualty failures in four different countries, we show that the asset side plays a determinant role in predicting life failures, while the liability side (and the income statement) are the most important criteria for non-life insurers. Asset mix (as captured by the part of fixed income instruments in the total investment portfolio) significantly predicts failure for life insurers, while operating inefficiency (operating and administrative expenses over total written premiums) appears to play no role at all. The opposite is true in the non-life sector: asset mix—highly significant in the life sector estimates—appears to play no role at all in non-life, while operating inefficiency is significant across all specifications.

We understand this stark contrast to be a consequence of the differences in balance sheet structure between the two sectors. Life insurers can spread profits and losses out over the course of several years, in line with their longer liability structure. Depending on the branch of activity, non-life insurers may have much shorter liability structures, meaning mismanagement (or, one or two bad years) may be enough to sink the firm given the ability of policyholders to lapse contracts more frequently. Non-life insurers have no smoothing mechanism to remain profitable in bad years, leaving them vulnerable to profitability shocks, while life insurance contracts can often work like a savings instrument with less of a role for active or efficient claims management.

Importantly, beyond the results which confirm the literature on a more comprehensive database, we are able to draw conclusions regarding cross-country differences as the coefficients vary across not only sectors but national jurisdictions. Our results suggest that operating inefficiency also matters more in jurisdictions with more concentrated markets (e.g., France), where firms may need to reduce their margins in response to a shock and whose profits may have been protected by their increased ability to set prices. In the non-life sector, we find that the protection afforded to insurers with a greater share of debt instruments can be mitigated in a jurisdictional context where unsustainable guarantees are offered to policyholders.

Regarding the policy and supervisory implications of our research, we provide evidence that insurance insolvencies do not come abruptly, as our indicators have some forward-looking properties. Insolvencies are predicted with a 3-year lag for ROA and 2-year lag for operating expenditure in P/C insurance. In the life sector, ROA predicts failure with a

1-year lag and the share of bond assets has predictive power with a 3-year lag. On the other hand, we do not find a confirmation that an acceleration of premium leads to difficulties a few years later. Macroeconomic variables play some role, confirming the literature, but it is not substantial and mainly concentrated on the level of interest rates. Here, such a variable is more a conditioning variable than one which highlights a transmission channel of vulnerabilities, as it may simply express the concentration of defaults at the beginning of our sample period.

A major contribution of this work is to uncover differences across countries, with a more significant effect of operational inefficiency (measured by operational expenditure ratio) in France characterized by more concentrated market. In addition, while we also confirm the protecting role of bond investments for life insurance, this is not supported by the Japanese case, stressing the limitations of such a ratio when guarantees on yield play a big role as was the case in Japan during the 1990-2000 period.

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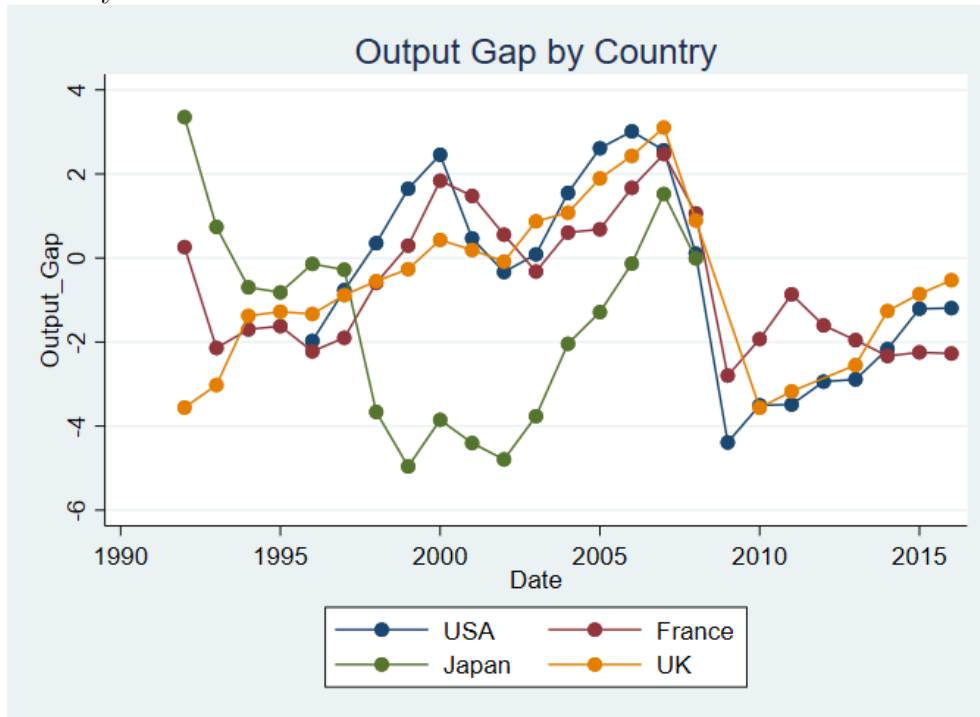
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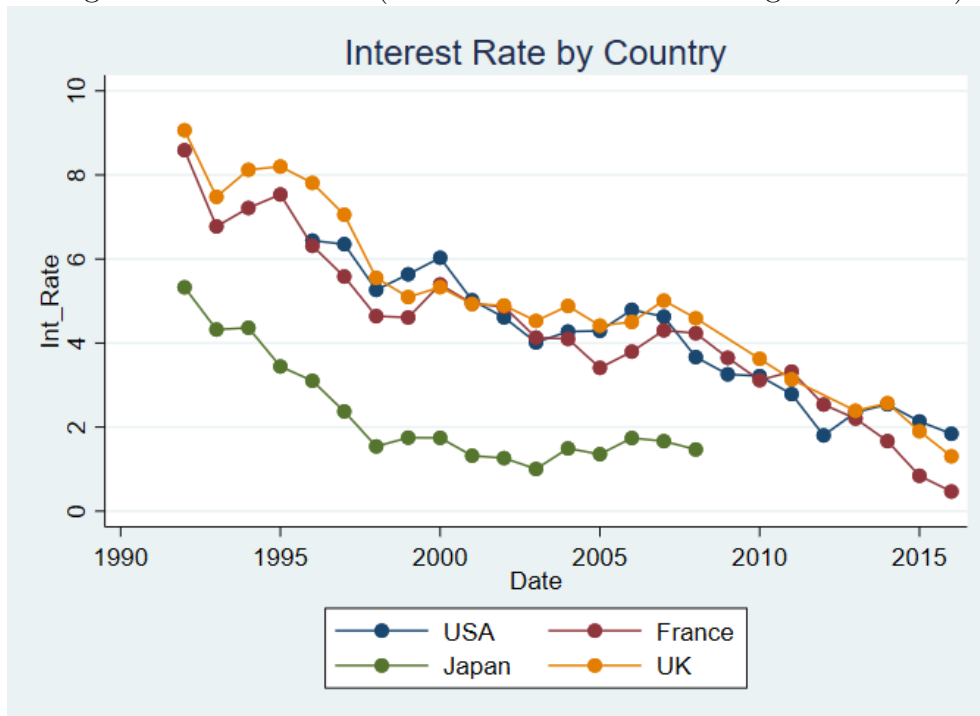
9 Figures

Figure 1.1: Output Gaps (Deviations of Actual GDP from Potential GDP as a % of Potential GDP, by Country.



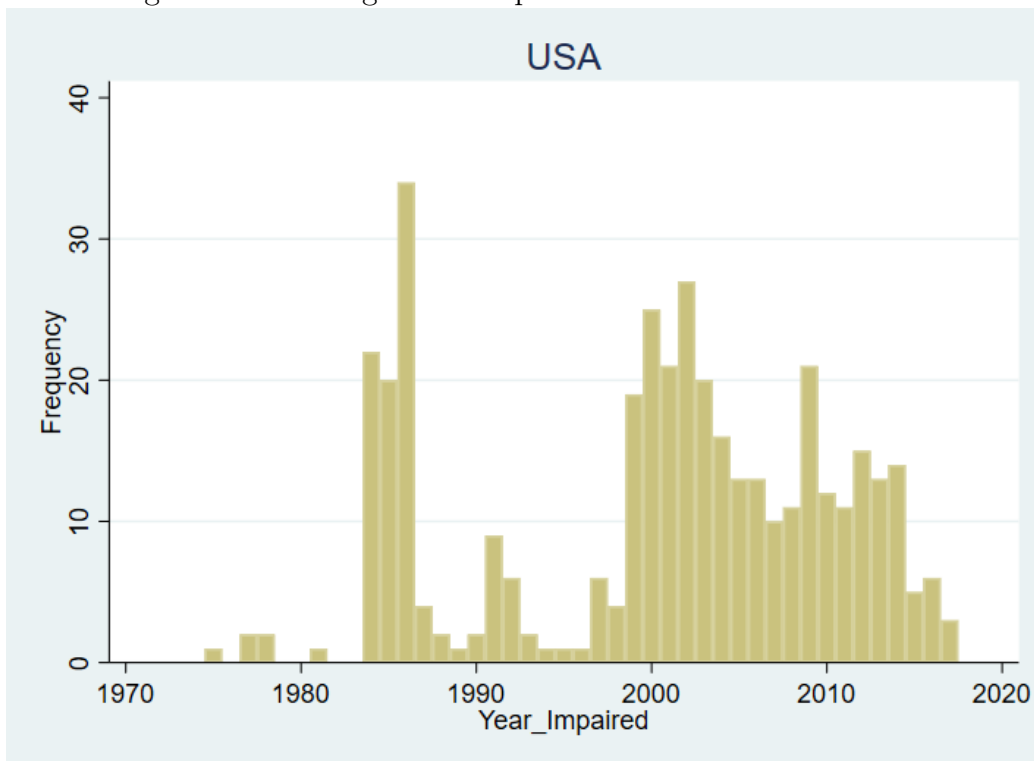
Note: This figure aims to provide information about the macroeconomic context of each country by showing the evolution of the output gaps of each country throughout the entirety of our sample. Most countries experience a busts in the early 1990s and 2008, while Japan's economy stagnated inbetween these two busts during the so-called Lost Decade. **Source:** OECD.

Figure 1.2: Long-term Interest Rates (Government Bonds Maturing in Ten Years) by country.



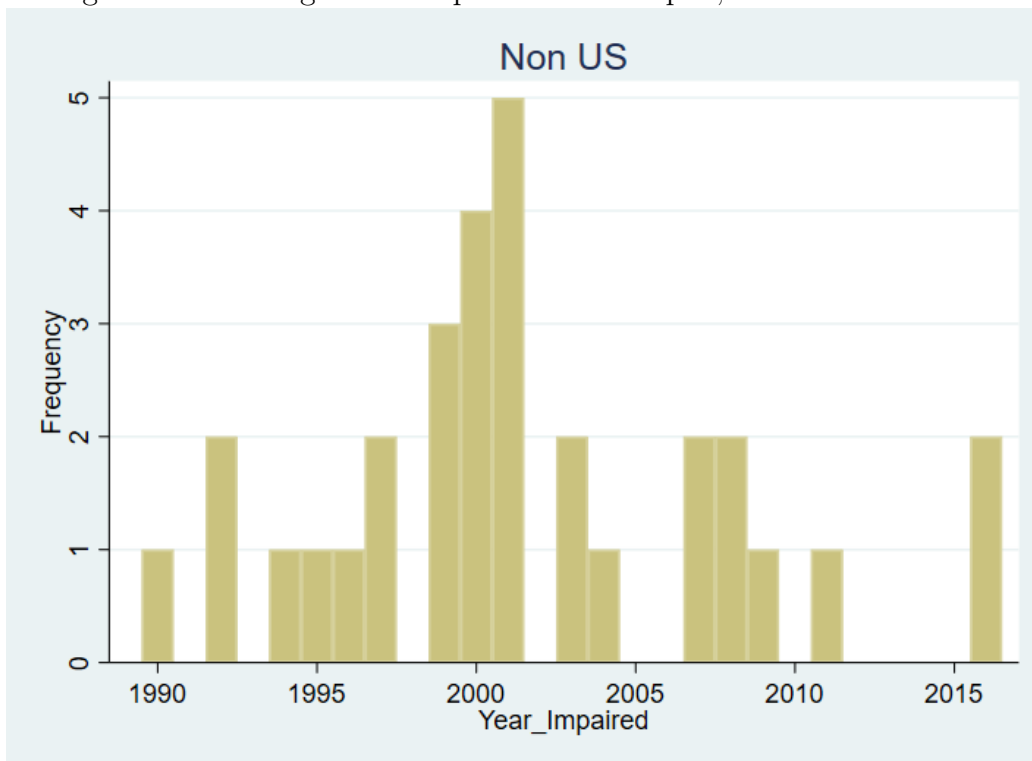
Note: This figure aims to provide information about the macroeconomic context of each country by showing the evolution of the long-term interest rates (government bonds maturing in 10 years) for each country throughout the entirety of our sample. Interest rates exhibit an essentially monotonic downward slope from higher rates in the 1990s to today's near-zero low rate environment. **Source:** OECD.

Figure 1.3: Histogram of Impairments in the United States



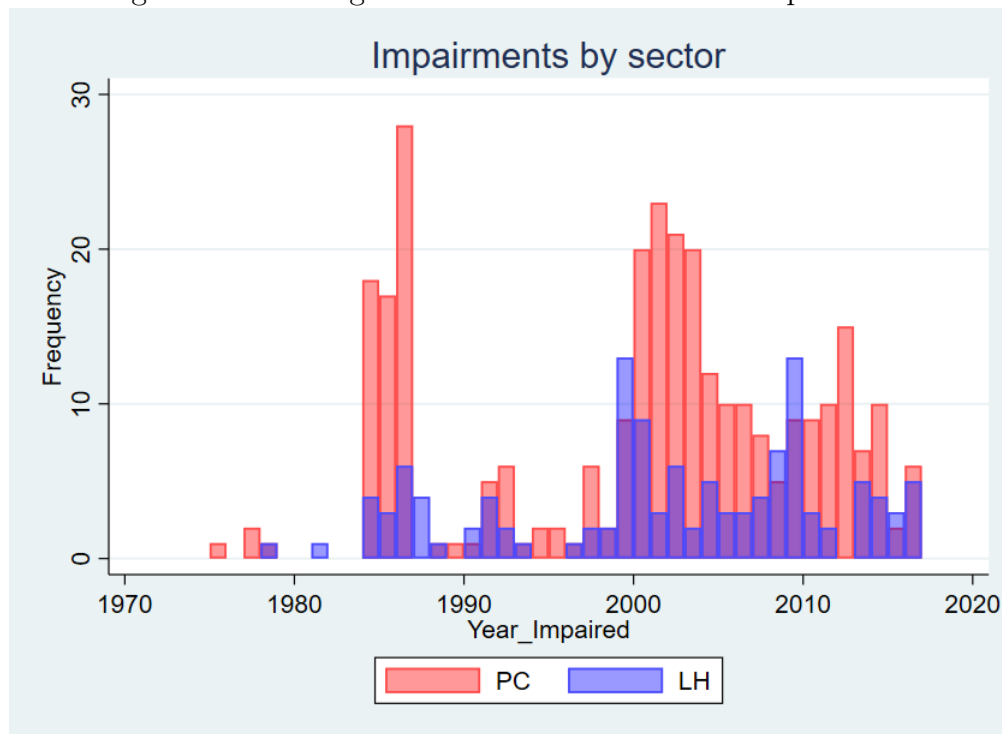
Note: This figure shows the frequency of impairments for all collected cases for the United States. A well documented increase in entry (coupled with a lack of adequately risk-based solvency requirements) lead to a large wave of firms amongst smaller firms in the late 1980s. While this country represents our richest data source, jurisdictional differences also lead to a higher number of failures compared with Europe, where portfolios are often transferred from struggling to healthy firms to avoid a full liquidation.

Figure 1.4: Histogram of Impairments in Japan, France and the UK



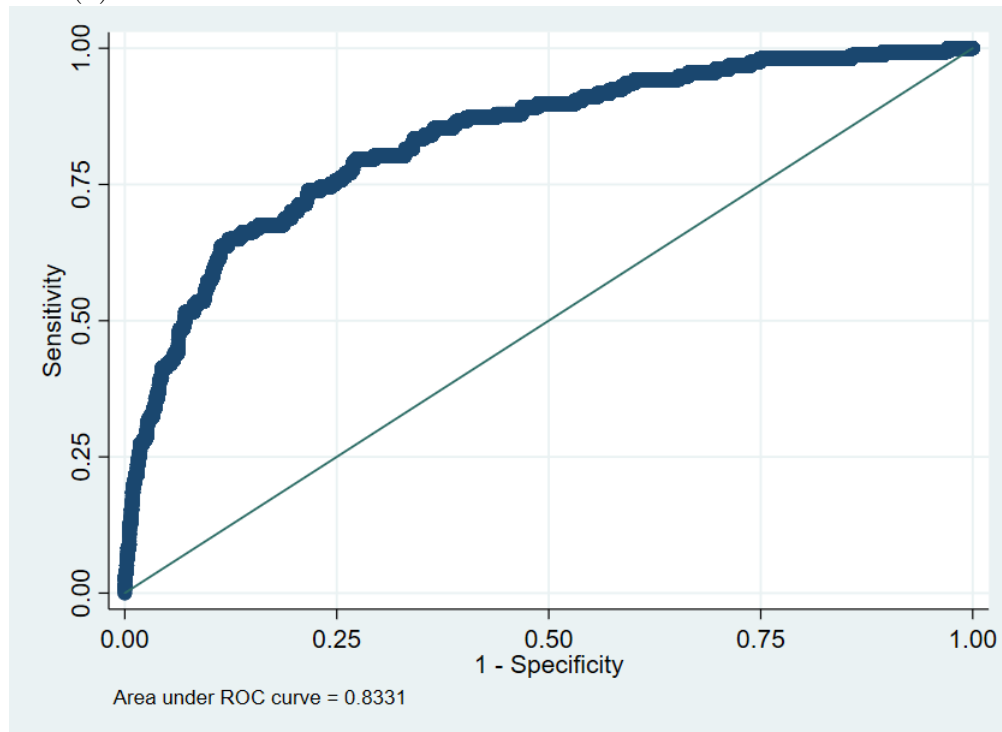
Note: This figure shows the frequency of non-US cases in our sample (France, Japan and UK). As in the US, we observe a spike around the year 2000, as well as a few notable larger scale failures (or, impairments requiring government bailout packages) around the 2008 crisis.

Figure 1.5: Histogram of Life versus Non-Life Impairments



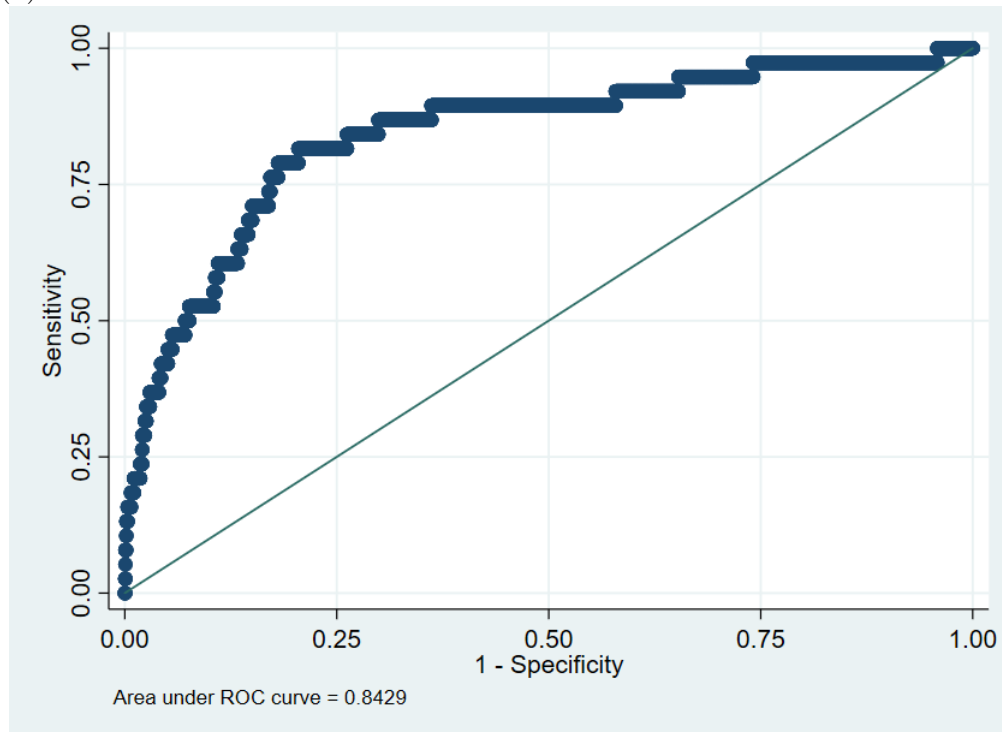
Note: This figure shows the frequency of impairments by sector of activity. Life failures appear more correlated with financial cycles, with peaks around the bust of the dot-com bubble of 2000-2001 and the 2008 financial crisis.

Figure 1.6: Receivership Operating Characteristic (ROC) Curves in the Non-Life sector, Specification (1).



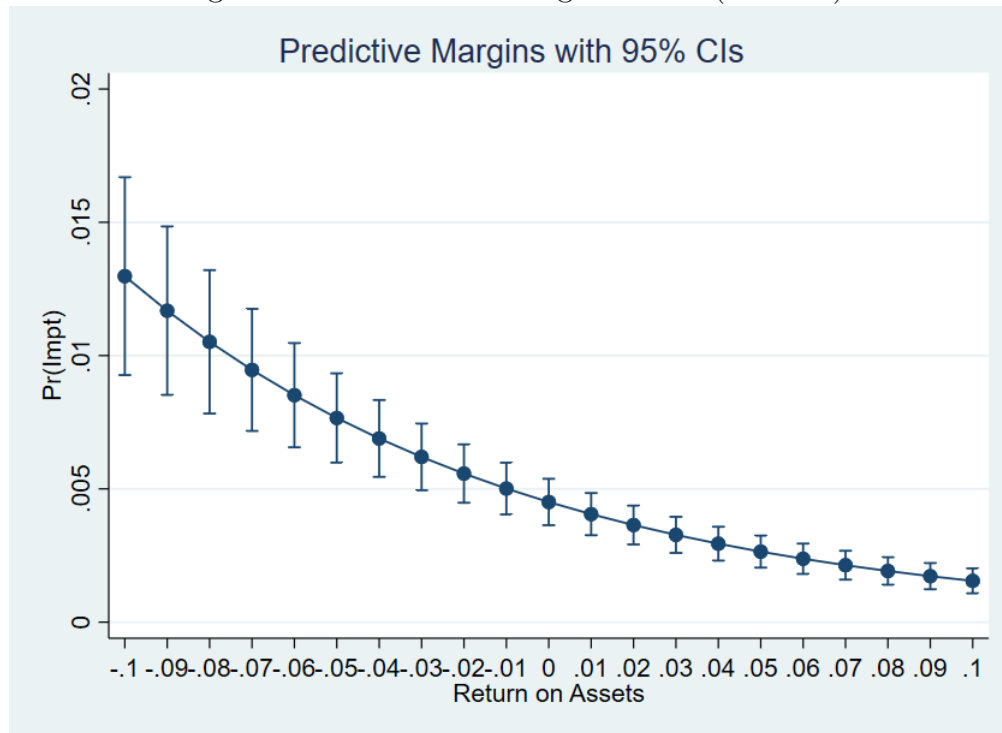
Note: The figure plots the true positive rate (*sensitivity*) as a function of the false positive rate ($1 - \textit{specificity}$) for our first logic specification in Table 1.4. Intuitively, the logistic regression first estimates a $\hat{p} \in (0, 1]$ for each observation. Each point on this graph represents the trade-off in catching true impairments versus misdiagnosing a healthy firms for this specification. The greater the area, the better the overall predictive power of the model. Our area under the curve (AUC) of ≈ 0.83 is in line with previous literature.

Figure 1.7: Receivership Operating Characteristic (ROC) Curves in the Life sector, Specification (1).



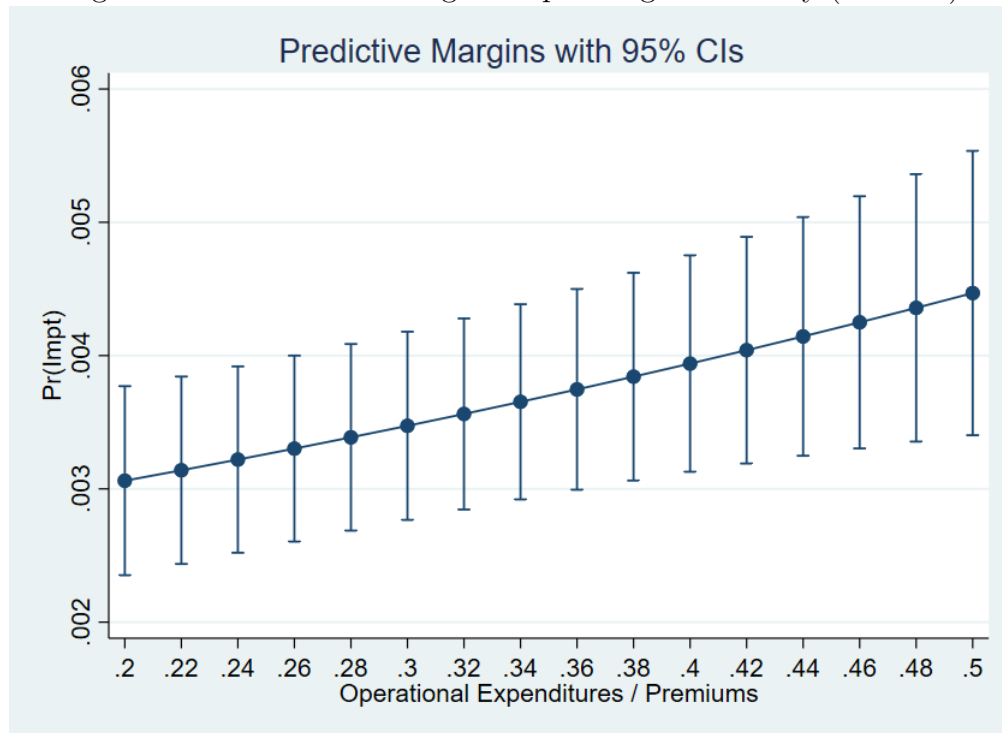
Note: The figure plots the true positive rate (*sensitivity*) as a function of the false positive rate ($1 - \textit{specificity}$) for our first logic specification in table 1.7. Intuitively, the logistic regression first estimates a $\hat{p} \in (0, 1]$ for each observation. Each point on this graph represents the trade-off in catching true impairments versus misdiagnosing a healthy firm for this specification. The greater the area, the better the overall predictive power of the model. Our area under the curve (AUC) of ≈ 0.84 is in line with previous literature.

Figure 1.8: Predictive Margins: ROA (Non-life)



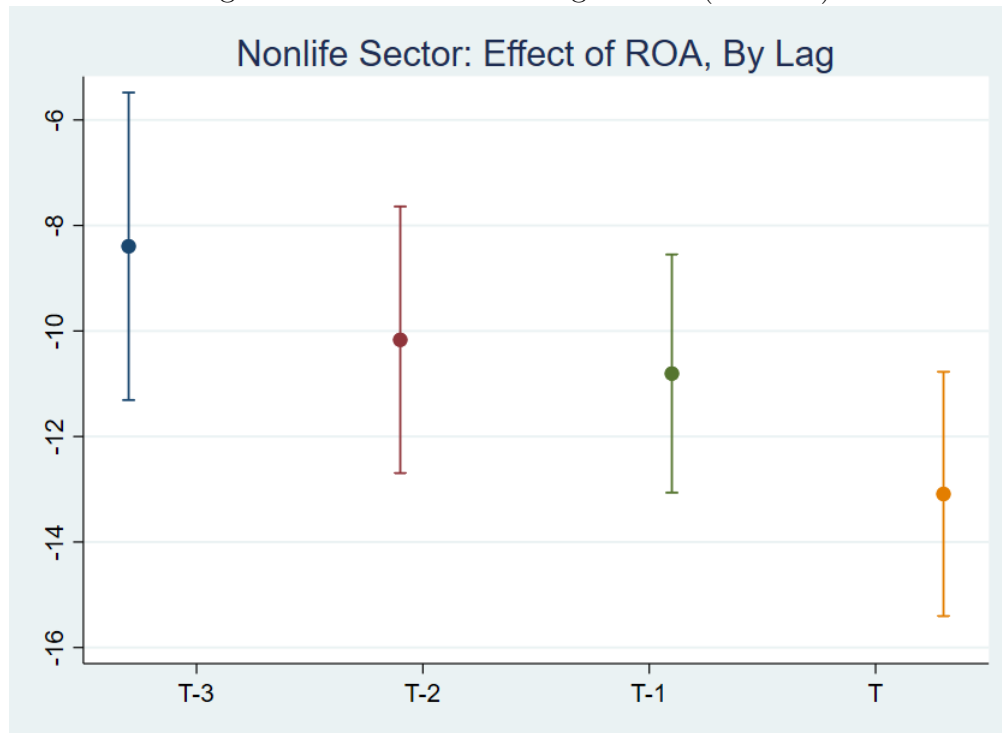
Note: This figure shows the average predicted probability of failure, \hat{p} for Logit models, if all observations had the indicated ROA levels (while holding other covariates at their sample means). The dot is the mean probability on the y-axis for a given level of ROA on the x-axis. 2 Standard errors are provided above and below the mean estimate. We observe a clear negative relationship between ROA and $Pr(Defaul)$, although higher ROA values exhibit tighter confidence intervals compared with lower ones.

Figure 1.9: Predictive Margins: Operating Inefficiency (Non-life)



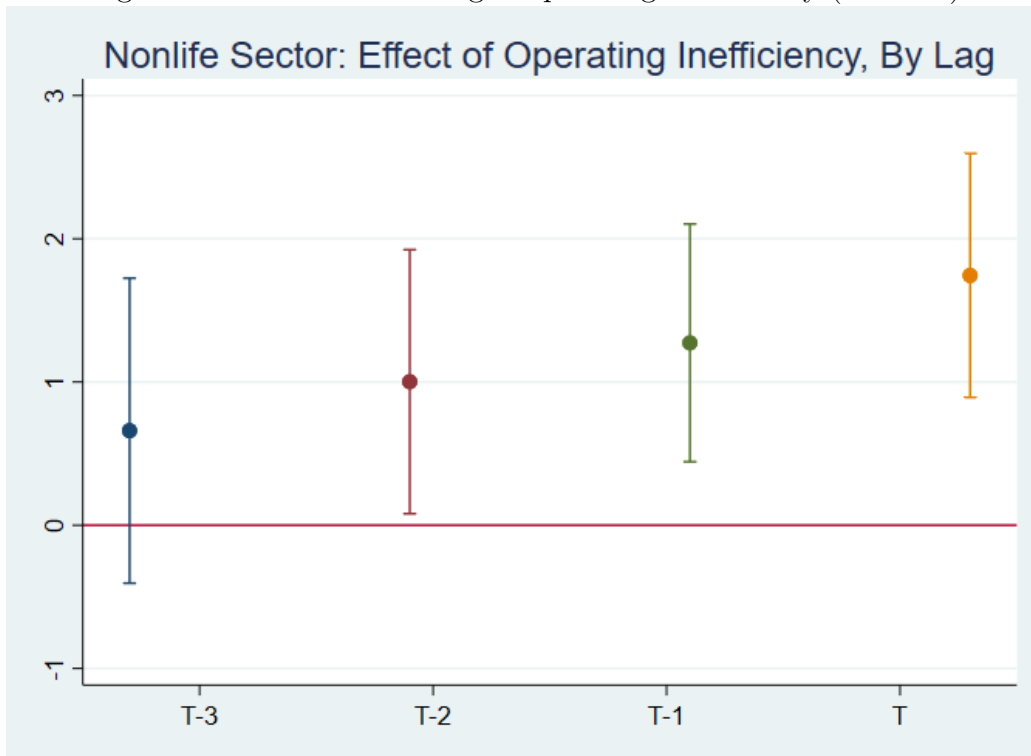
Note: This figure shows the average predicted probability of failure, \hat{p} for Logit models, if all observations had the indicated Operating Inefficiency levels (while holding other covariates at their sample means). The dot is the mean probability on the y-axis for a given level of Operating Inefficiency on the x-axis. 2 standard errors are provided above and below the mean estimate. We observe a positive relationship between Operating Inefficiency and $Pr(Default)$, although with very large confidence intervals.

Figure 1.10: Additional Lags: ROA (Non-life)



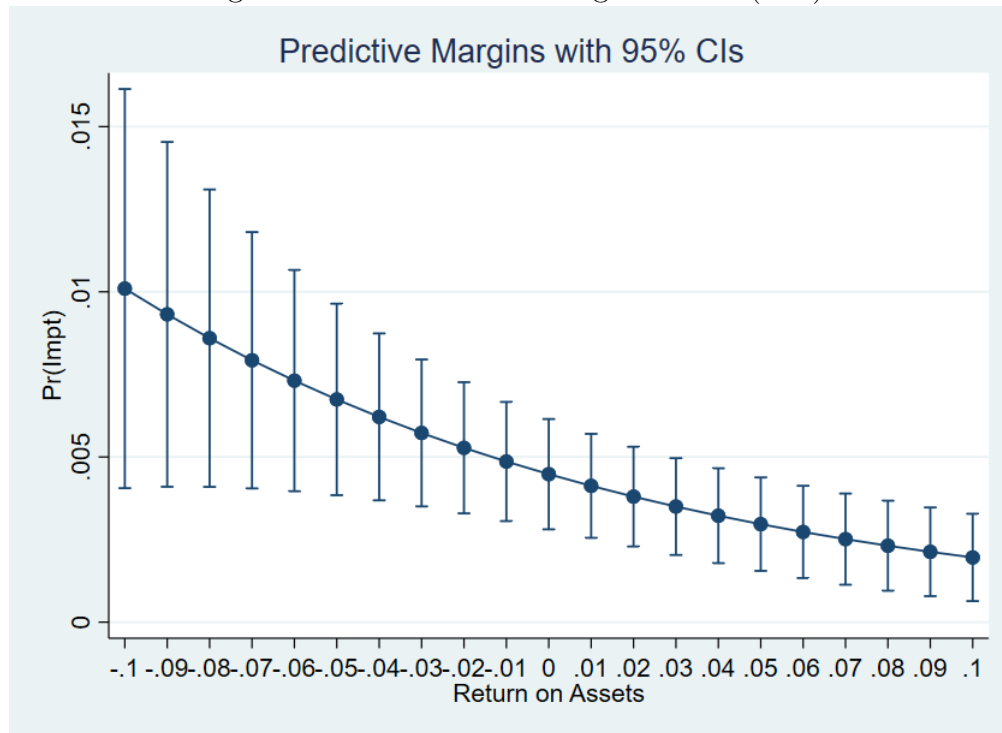
Note: This figure shows the coefficient values (and 95 % confidence intervals) for a key variable of interest (ROA) by lag. In the non-life sector, ROA is a significant predictor of failure up to three years in advance of the event, implying a fragility to profitability shocks.

Figure 1.11: Additional Lags: Operating Inefficiency (Non-life)



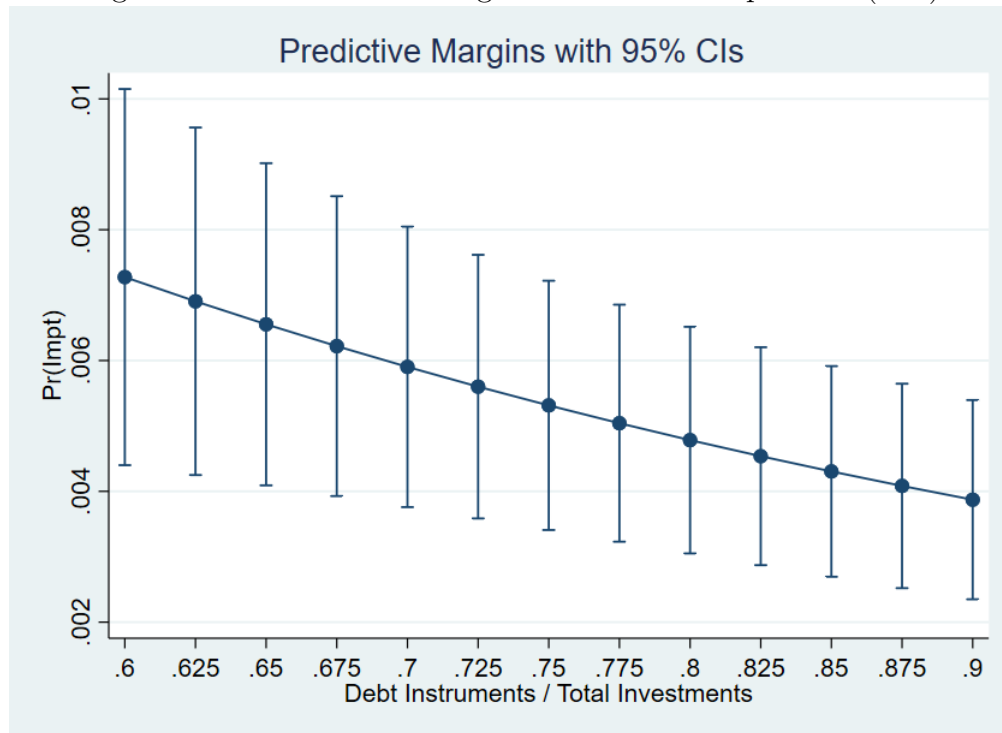
Note: This figure shows the coefficient values (and 95 % confidence intervals) for a key variable of interest (Operating Inefficiency) by lag. In the non-life sector, this variable becomes significant two years before the failure event.

Figure 1.12: Predictive Margins: ROA (Life)



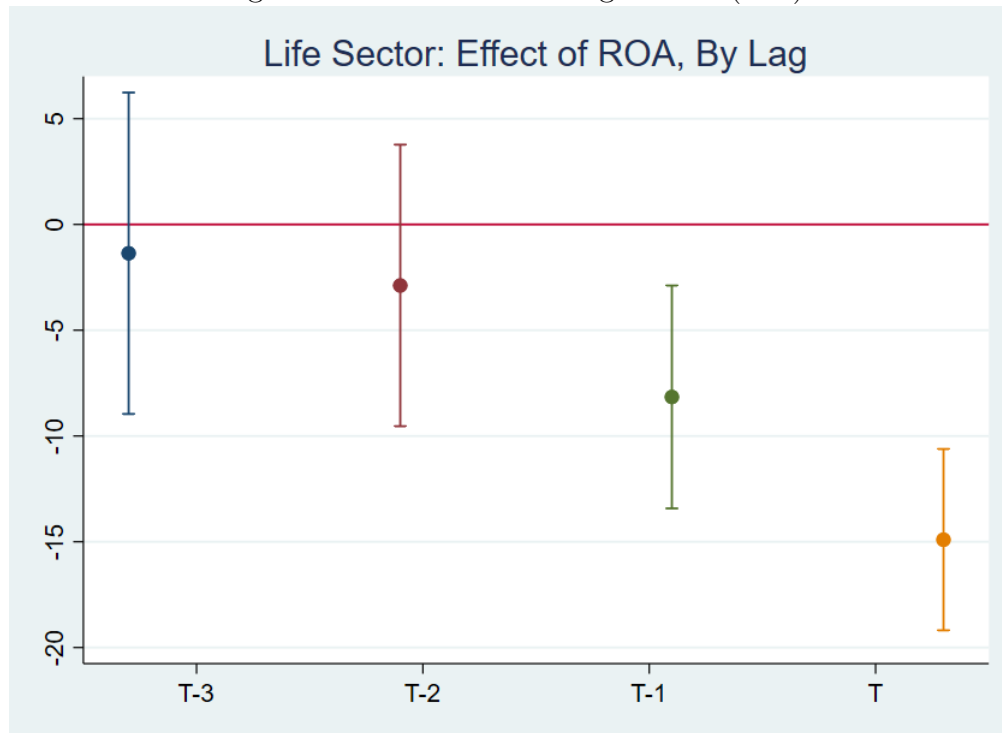
Note: This figure shows the average predicted probability of failure, \hat{p} for Logit models, if all observations had the indicated ROA levels (while holding other covariates at their sample means). The dot is the mean probability on the y-axis for a given level of ROA on the x-axis. 2 Standard errors are provided above and below the mean estimate. We observe a clear negative relationship between ROA and $Pr(Default)$, although higher ROA values exhibit tighter confidence intervals compared with low ones. Confidence bands for this measure are universally higher in the life sector, demonstrating the importance of other variables.

Figure 1.13: Predictive Margins: Portfolio Composition (Life)



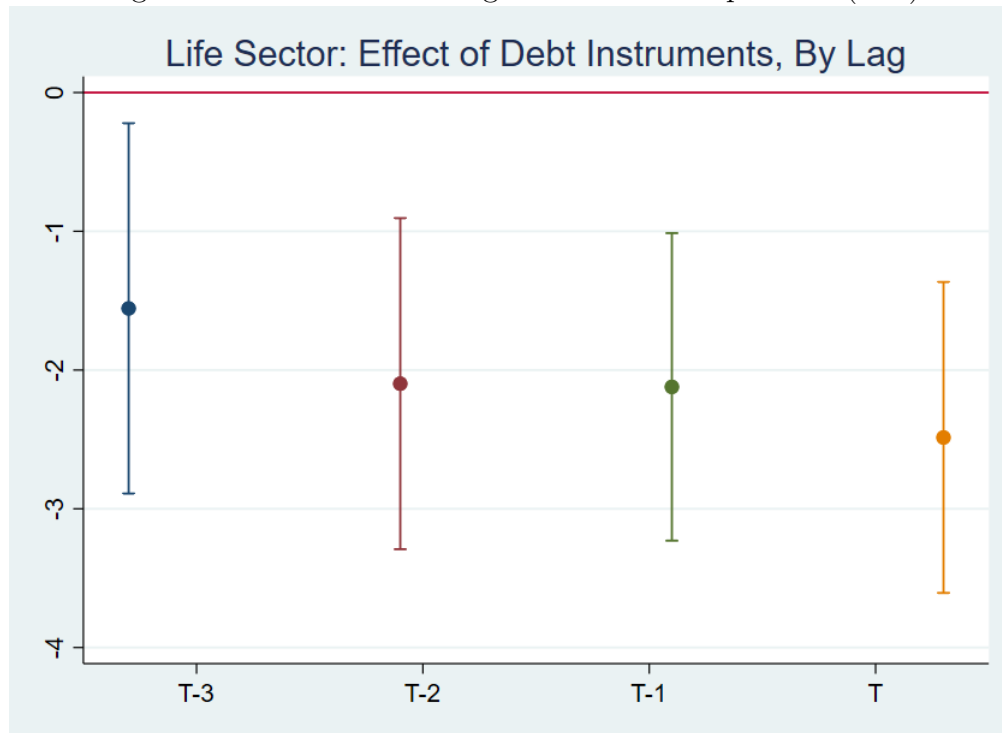
Note: This figure shows the average predicted probability of failure, \hat{p} for Logit models, if all observations had the indicated Debt instrument share level (while holding other covariates at their sample means). The dot is the mean probability on the y-axis for a given level of Debt instrument share on the x-axis. 2 Standard errors are provided above and below the mean estimate. We observe a clear negative relationship between the predominance of fixed income instruments and $Pr(Default)$, although large confidence intervals render it difficult to analyze at the margin.

Figure 1.14: Additional Lags: ROA (Life)



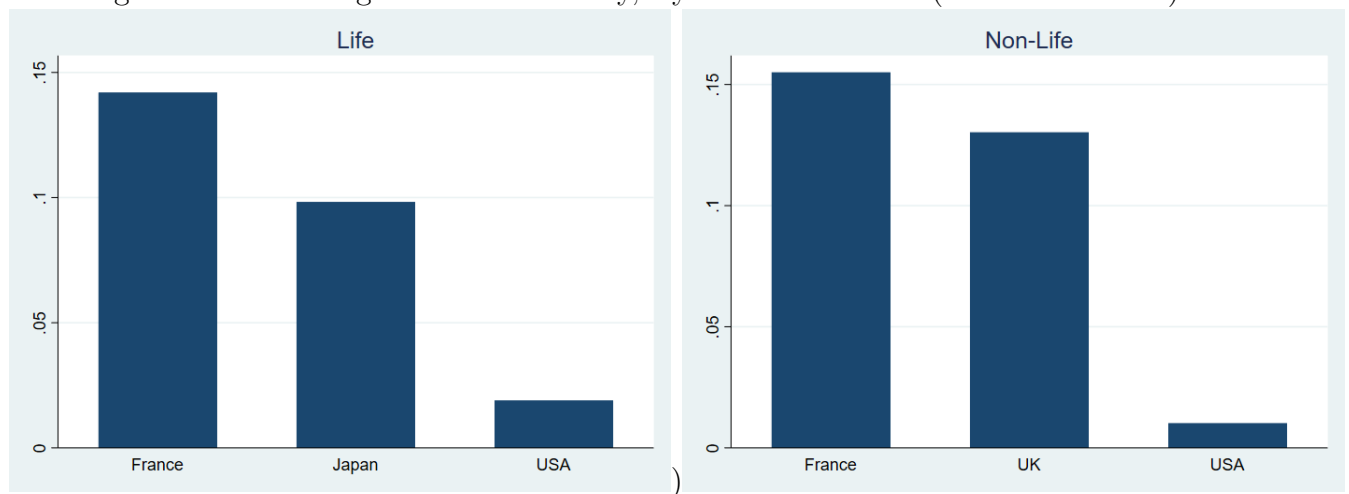
Note: This figure shows the coefficient values (and 95 % confidence intervals) for a key variable of interest (ROA) by lag. In the life sector, ROA is a significant predictor of failure only in the year before the event, reflecting the sectors ability to smooth profitability shocks over several periods. This sector overall appears less vulnerable to profitability shocks.

Figure 1.15: Additional Lags: Portfolio Composition (Life)



Note: This figure shows the coefficient values (and 95 % confidence intervals) for a key variable of interest (Debt Instruments Share) by lag. In the life sector, the share of fixed income instruments in an insurer's portfolio is a significant predictor of failure even three years before the event, underscoring such instruments' resilience to financial cycles. Life insurers tend to hold such instruments to maturity, therefore receiving a contractually agreed upon return for the life of the instrument.

Figure 1.16: Average HHI Per Country, By Line of Business (Gross Premiums)



Note: These figures show the average HHIs values, calculated on the database based on SNL data by year and by line of business (life / non-life) as captured by gross premiums over the course of the available sample by country. For instance, the first bar from the left shows the average yearly HHI values of the life insurance industry in France in our dataset.

10 Tables

Table 1.1: Summary Statistics with T-test, Impaired vs. Healthy Firms (All Countries).

	(1)		(2)		(3)	
	<i>Impaired</i>		<i>Healthy</i>		<i>Difference</i>	
	mean	sd	mean	sd	b	t
Avg T.A.	783,237	4,412,327	2,535,669	18,310,035	1,752,432***	(5.01)
Avg T.A. (US)	231,992	1,180,281	1,645,429	12,488,521	1,413,437***	(8.34)
Avg T.A. (Other)	6,009,040	12,906,406	43,880,341	83,438,740	37,871,301***	(5.15)
Observations	263		6,974		7,236	

Note: This table of summary statistics shows a t-test of main variables comparing target (acquired) companies to the rest of the market. These firms, like acquirers, appear slightly larger than average (and more diversified across lines of business), although still significantly smaller than acquirers on average.

Table 1.2: Summary Statistics of Financial Ratios, Impaired vs. Healthy Firms (All countries).

	(1)		(2)		(3)	
	<i>Impaired</i>		<i>Healthy</i>		<i>Difference</i>	
	mean	sd	mean	sd	b	t
ROA	-0.02	0.05	0.02	0.05	0.04***	(13.00)
ROE	-0.05	0.16	0.04	0.13	0.09***	(8.67)
ROA Volatility	0.06	0.04	0.05	0.04	-0.02***	(-6.68)
ROE Volatility	0.19	0.11	0.13	0.10	-0.06***	(-9.17)
Loss Ratio	0.50	0.22	0.42	0.20	-0.08***	(-4.95)
Reinsurance Ceded	0.32	0.21	0.32	0.23	-0.01	(-0.52)
Debt Investments	0.77	0.27	0.85	0.22	0.08***	(4.77)
Equity Investments	0.17	0.22	0.17	0.26	-0.00	(-0.15)
Real Estate Investments	0.07	0.15	0.03	0.11	-0.04***	(-4.43)
Operating Inefficiency	0.37	0.22	0.36	0.32	-0.01	(-0.45)
Observations	263		6593		6856	

Note: In the table, figures are displayed as decimals (e.g., 0.05 represents an ROA of 5%).

Table 1.3: Summary Statistics of Financial Ratios, Impaired vs. Healthy Firms, Separated by Sector.

	(1)		(2)		(3)	
	<i>Impaired</i>		<i>Healthy</i>		<i>Difference</i>	
	mean	sd	mean	sd	b	t
ROA	-0.02	0.05	0.02	0.04	0.04***	(10.28)
ROE	-0.04	0.13	0.03	0.10	0.08***	(8.30)
ROA Volatility	0.07	0.04	0.04	0.03	-0.03***	(-9.38)
ROE Volatility	0.18	0.11	0.11	0.08	-0.08***	(-9.33)
Loss Ratio	0.50	0.22	0.41	0.20	-0.09***	(-5.05)
Reinsurance Ceded	0.34	0.20	0.32	0.24	-0.03	(-1.55)
Debt Investments	0.77	0.26	0.83	0.21	0.06**	(3.12)
Equity Investments	0.17	0.20	0.18	0.25	0.02	(0.98)
Real Estate Investments	0.06	0.13	0.02	0.08	-0.04***	(-4.21)
Operating Inefficiency	0.38	0.17	0.36	0.24	-0.02	(-1.26)
Observations	183		3358		3541	

	(1)		(2)		(3)	
	<i>Impaired</i>		<i>Healthy</i>		<i>Difference</i>	
	mean	sd	mean	sd	b	t
ROA	-0.03	0.06	0.02	0.06	0.05***	(7.52)
ROE	-0.05	0.23	0.05	0.16	0.10***	(3.90)
ROA Volatility	0.05	0.05	0.05	0.05	-0.00	(-0.45)
ROE Volatility	0.21	0.11	0.15	0.12	-0.07***	(-4.88)
Reinsurance Ceded	0.13	0.19	0.17	0.19	0.04	(1.32)
Debt Investments	0.75	0.28	0.86	0.24	0.11***	(3.46)
Equity Investments	0.17	0.24	0.15	0.26	-0.03	(-0.96)
Real Estate Investments	0.09	0.18	0.04	0.14	-0.05*	(-2.43)
Operating Inefficiency	0.34	0.32	0.36	0.46	0.02	(0.55)
Observations	80		3217		3297	

Note: Non-life firms are shown above, and life firms are shown below.

Table 1.4: Logistic Regression Estimates (Non-life Sector).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ROA_{t-1}	-10.86*** (-9.37)	-10.81*** (-9.39)	-10.51*** (-9.28)	-10.86*** (-9.37)	-10.87*** (-9.42)		
ROE_{t-1}						-3.531*** (-9.16)	-3.531*** (-9.16)
$Size$	-0.122* (-2.42)	-0.124* (-2.51)	-0.104* (-2.19)	-0.122* (-2.42)	-0.121* (-2.42)	-0.163** (-3.13)	-0.163** (-3.13)
$DebtIns_{t-1}$	-0.243 (-0.72)	-0.344 (-1.04)	-0.615 (-1.94)	-0.243 (-0.72)	-0.314 (-0.94)	-0.373 (-1.07)	-0.373 (-1.07)
$LossRatio_{t-1}$	1.192** (2.73)	1.153** (2.67)	1.516*** (3.63)	1.192** (2.73)	1.129** (2.61)	0.897 (1.93)	0.897 (1.93)
$Reins_{t-1}$	1.767*** (3.83)	1.744*** (3.84)	2.072*** (4.65)	1.767*** (3.83)	1.713*** (3.76)	1.790*** (3.77)	1.790*** (3.77)
$OpExp_{t-1}$	1.286** (3.01)	1.273** (3.01)	1.387*** (3.30)	1.286** (3.01)	1.267** (2.98)	1.420** (3.25)	1.420** (3.25)
$10YRIIntRate_{t-1}$			0.518*** (6.88)	2.819 (0.33)	-0.147 (-0.08)		3.558 (0.41)
$\Delta 10YRIIntRate_{t-1}$			-0.0185 (-0.17)	-1.132 (-0.37)	0.0289 (0.03)		-1.473 (-0.48)
$OutputGap_{t-1}$			-0.0207 (-0.50)	2.173 (0.18)	-1.368 (-0.97)		3.020 (0.25)
Country-Year Fixed Effect	Yes	No	No	Yes	No	Yes	Yes
Year Fixed Effect	No	Yes	No	No	Yes	No	No
Country Fixed Effect	No	Yes	No	No	Yes	No	No
AIC	1,726.6	1,736.6	1,771.2	1,726.6	1,739.8	1,626.1	1,626.1
Pseudo R2	0.146	0.142	0.122	0.146	0.144	0.137	0.137
Observations	28,801	28,930	32,059	28,801	28,930	28,685	28,685

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The table displays the results for different specifications of equation 1.1, which models the probability of failure in the non-life sector. The different columns vary in terms of explanatory variables and fixed effects as described in the bottom of the table.

Table 1.5: Cross-country Logistic Regression Estimates (Non-Life Sector).

	(1)	(2)	(3)
ROA_{t-1}	-10.51*** (-9.28)	-10.55*** (-9.29)	-10.83*** (-9.61)
France $\times ROA_{t-1}$		19.76 (0.55)	
UK $\times ROA_{t-1}$		4.279 (0.23)	
$Size$	-0.104* (-2.19)	-0.104* (-2.18)	-0.119* (-2.44)
$DebtIns_{t-1}$	-0.615 (-1.94)	-0.617 (-1.94)	-0.424 (-1.32)
$LossRatio_{t-1}$	1.516*** (3.63)	1.521*** (3.63)	1.296** (3.12)
$Reins_{t-1}$	2.072*** (4.65)	2.068*** (4.62)	1.882*** (4.28)
$OpExp_{t-1}$	1.387*** (3.30)	1.377** (3.27)	1.313** (3.10)
France $\times OpExp_{t-1}$			6.368*** (5.02)
UK $\times OpExp_{t-1}$			2.134 (1.53)
$10YRIntRate_{t-1}$	0.518*** (6.88)	0.522*** (6.87)	0.459*** (6.23)
$\Delta 10YRIntRate_{t-1}$	-0.0185 (-0.17)	-0.0199 (-0.18)	-0.0305 (-0.29)
$OutputGap_{t-1}$	-0.0207 (-0.50)	-0.0212 (-0.51)	-0.00465 (-0.11)
Country-Year Fixed Effect	No	No	No
Year Fixed Effect	No	No	No
Country Fixed Effect	No	No	No
AIC	1,771.2	1,774.7	1,758.4
Pseudo R2	0.122	0.122	0.130
Observations	32,059	32,059	32,059

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table compares life sector failure dynamics across European and US jurisdictions.

Table 1.6: Parametric Survival Analysis Estimates with Time-Varying Covariates (Non-Life Sector).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ROA	-12.137*** (1.112)			-12.276*** (1.096)	8.663*** (1.215)	-12.093*** (1.087)	8.663*** (1.093)
Size	-0.106 (0.054)	-0.162** (0.059)	-0.176** (0.058)	-0.092 (0.053)	0.076* (0.038)	-0.106* (0.050)	0.076* (0.036)
DebtIns	-0.646 (0.340)	-0.900* (0.378)	-0.858* (0.373)	-0.739* (0.333)	0.503* (0.248)	-0.702* (0.339)	0.503* (0.248)
LossRatio	2.112*** (0.383)	2.100*** (0.449)	2.307*** (0.427)	2.182*** (0.374)	-1.561*** (0.310)	2.179*** (0.350)	-1.561*** (0.279)
Reins	2.899*** (0.422)	2.990*** (0.472)	3.031*** (0.458)	2.881*** (0.418)	-2.085*** (0.362)	2.910*** (0.375)	-2.085*** (0.335)
OpExp	1.498*** (0.405)	1.330** (0.476)	1.178* (0.467)	1.375*** (0.399)	-0.995** (0.305)	1.389*** (0.338)	-0.995*** (0.260)
OutputGap	0.062 (0.126)	0.072 (0.136)	-0.004 (0.051)	-0.017 (0.049)	0.007 (0.034)	-0.009 (0.041)	0.007 (0.029)
IntRate	0.603*** (0.149)	0.650*** (0.158)	0.696*** (0.110)	0.430*** (0.090)	-0.457*** (0.063)	0.638*** (0.098)	-0.457*** (0.055)
ROE		-4.047*** (0.368)	-3.967*** (0.355)				
Model	Cox PH	Cox PH	PH	PH	AFT	PH	AFT
Distribution			Weibull	Exponential	Weibull	Weibull	Weibull
Cluster?	No	No	No	No	No	Firm	Firm
AIC	1,558.1	1,252.4	757.4	894.6	887.5	887.5	887.5
Observations	33,376	33,196	33,196	33,376	33,376	33,376	33,376

Note: The table displays the estimated coefficients of Equations 1.2 and 1.3, which model the probability of failures of non life-insurers. The underlying probability distribution, estimated survival equation and error clustering specifications are indicated in the bottom of the table.

Table 1.7: Logistic Regression Estimates (Life sector).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ROA_{t-1}	-8.973** (-3.28)	-8.700** (-3.20)	-9.029*** (-3.81)	-8.973** (-3.28)	-9.015** (-3.29)		
ROE_{t-1}						-3.686*** (-5.82)	-3.686*** (-5.82)
$Size$	-0.127 (-1.60)	-0.130 (-1.64)	-0.0229 (-0.35)	-0.127 (-1.60)	-0.126 (-1.58)	-0.151 (-1.80)	-0.151 (-1.80)
$DebtIns_{t-1}$	-2.193*** (-3.78)	-2.167*** (-3.79)	-2.445*** (-4.59)	-2.193*** (-3.78)	-2.195*** (-3.79)	-1.790** (-2.83)	-1.790** (-2.83)
$Reins_{t-1}$	-0.411 (-0.45)	-0.000736 (-0.00)	-0.252 (-0.30)	-0.411 (-0.45)	-0.356 (-0.39)	-0.755 (-0.73)	-0.755 (-0.73)
$OpExp_{t-1}$	0.00687 (0.02)	0.0418 (0.10)	0.172 (0.45)	0.00687 (0.02)	0.0162 (0.04)	0.153 (0.34)	0.153 (0.34)
$10YRIntRate_{t-1}$			-0.0428 (-0.25)	-0.568 (-0.56)	9.952 (0.92)		-1.038 (-0.95)
$\Delta 10YRIntRate_{t-1}$			-0.134 (-0.56)	0.282 (0.32)	-15.65 (-1.36)		0.996 (0.97)
$OutputGap_{t-1}$			0.0980 (1.14)	0.296 (1.31)	-0.0377 (-0.07)		0.334 (1.46)
Country-Year Fixed Effect	Yes	No	No	Yes	No	Yes	Yes
Year Fixed Effect	No	Yes	No	No	Yes	No	No
Country Fixed Effect	No	Yes	No	No	Yes	No	No
AIC	437.4	448.9	492.9	437.4	447.4	378.6	378.6
Pseudo R2	0.158	0.159	0.073	0.158	0.175	0.201	0.201
Observations	6,751	6,892	10,215	6,751	6,892	6,637	6,637

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: The table displays the results for different specifications of equation 1.1, which models the probability of failure in the life sector. The different columns vary in terms of explanatory variables and fixed effects as described in the bottom of the table.

Table 1.8: Cross-country Logistic Regression Estimates (Life Sector).

	(1)	(2)	(3)
ROA_{t-1}	-8.910*** (-3.76)	-9.268*** (-3.89)	-8.271*** (-3.43)
Japan $\times ROA_{t-1}$		23.79 (0.65)	
$Size$	-0.0580 (-0.94)	-0.0641 (-1.02)	-0.117 (-1.74)
$DebtIns_{t-1}$	-2.361*** (-4.35)	-2.350*** (-4.25)	-2.328*** (-4.28)
Japan $\times DebtIns_{t-1}$			1.992** (2.80)
$Reins_{t-1}$	-0.568 (-0.64)	-0.553 (-0.62)	-0.251 (-0.28)
$OpExp_{t-1}$	0.194 (0.50)	0.205 (0.53)	0.164 (0.41)
$10YRIntRate_{t-1}$	-0.0756 (-0.45)	-0.101 (-0.60)	0.00734 (0.04)
$\Delta 10YRIntRate_{t-1}$	-0.0815 (-0.33)	-0.0597 (-0.25)	-0.130 (-0.53)
$OutputGap_{t-1}$	0.0671 (0.78)	0.0635 (0.74)	0.0593 (0.69)
Country-Year Fixed Effect	No	No	No
Year Fixed Effect	No	No	No
Country Fixed Effect	No	No	No
AIC	485.7	486.7	481.5
Pseudo R2	0.073	0.075	0.086
Observations	10,716	10,716	10,716

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: This table compares non-life failure dynamics across Japanese and US jurisdictions.

Table 1.9: Parametric Survival Estimates with Time-Varying Covariates (Life Sector).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ROA	-13.870*** (1.973)		-14.035*** (1.891)		5.517*** (1.314)	-14.035*** (1.569)	5.517*** (1.382)
Size	0.027 (0.063)	-0.001 (0.081)	0.034 (0.063)	0.009 (0.081)	-0.013 (0.025)	0.034 (0.059)	-0.013 (0.025)
DebtIns	-2.577*** (0.532)	-3.245*** (0.653)	-2.466*** (0.538)	-3.291*** (0.651)	0.970*** (0.293)	-2.466*** (0.557)	0.970** (0.337)
Reins	-0.072 (0.834)	-0.496 (1.139)	-0.173 (0.841)	-0.402 (1.125)	0.068 (0.330)	-0.173 (0.794)	0.068 (0.315)
OpExp	0.321 (0.332)	0.225 (0.411)	0.292 (0.332)	0.291 (0.406)	-0.115 (0.134)	0.292 (0.338)	-0.115 (0.138)
IntRate	0.161 (0.307)	0.111 (0.501)	0.601** (0.232)	-0.088 (0.185)	-0.236*** (0.063)	0.601* (0.253)	-0.236*** (0.063)
OutputGap	-0.140 (0.131)	-0.114 (0.186)	0.019 (0.078)	0.149 (0.117)	-0.007 (0.030)	0.019 (0.083)	-0.007 (0.032)
ROE		-2.564*** (0.773)		-2.567*** (0.772)			
Model	Cox PH	Cox PH	PH	PH	AFT	PH	AFT
Distribution			Weibull	Exponential	Weibull	Weibull	Weibull
Cluster?	No	No	No	No	No	Firm	Firm
AIC	422.5	264.5	280.5	200.3	280.5	280.5	280.5
Observations	11,814	11,541	11,814	11,541	11,814	11,814	11,814

Note: The table displays the estimated coefficients of Equations 1.2 and 1.3, which model the probability of failures of life insurers. The underlying probability distribution, estimated survival equation and error clustering specifications are indicated in the bottom of the table.

Table 1.10: Additional Lags (Property-casualty Sector)

	(T-3)	(T-2)	(T-1)	(T)
ROA	-8.395*** (-5.65)	-10.17*** (-7.88)	-10.81*** (-9.39)	-13.09*** (-11.08)
DebtIns	-0.747* (-2.08)	-0.420 (-1.20)	-0.344 (-1.04)	-0.624 (-1.72)
OpExp	0.660 (1.21)	1.002* (2.13)	1.273** (3.01)	1.744*** (4.01)
Country FE and Year FE	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Pseudo R2	0.084	0.110	0.142	0.216
Observations	23,035	25,088	28,930	30,216

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.11: Additional Lags (Life Sector)

	(T-3)	(T-2)	(T-1)	(T)
ROA	-1.362 (-0.35)	-2.884 (-0.85)	-8.156** (-3.03)	-14.90*** (-6.82)
DebtIns	-1.556* (-2.29)	-2.098*** (-3.45)	-2.121*** (-3.75)	-2.486*** (-4.35)
OpExp	0.394 (0.91)	0.613 (1.68)	0.114 (0.28)	0.374 (1.00)
Country FE and Year FE	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes
Pseudo R2	0.121	0.152	0.154	0.198
Observations	6,045	7,416	8,046	8,921

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.12: Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>ROA</i> _{<i>t</i>-1}	-8.477*** (-10.58)	-7.839*** (-5.46)	-8.053*** (-4.73)	-8.428*** (-4.63)	-6.228* (-2.36)	-6.228* (-2.36)	-5.093 (-1.87)
<i>DebtIns</i> _{<i>t</i>-1}	-0.704** (-3.22)	-0.110 (-0.26)	-0.435 (-0.92)	-0.479 (-0.98)	-1.868** (-3.24)	-1.868** (-3.24)	-1.968*** (-3.30)
<i>OpExp</i> _{<i>t</i>-1}		1.819*** (3.33)	2.411*** (3.68)	2.111** (2.93)	0.0568 (0.14)	0.0568 (0.14)	0.115 (0.27)
<i>PremGrowth</i> _{<i>t</i>-1}				-0.139 (-0.95)			-0.0929 (-0.45)
Country FE and Year FE	Yes	Yes	Yes	Yes	Yes		Yes
Size	All	Above 10M	Above 20M	All	Above 10M	All	All
Sector	All	PC	PC	PC	LH	LH	LH
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.139	0.206	0.238	0.239	0.157	0.157	0.160
Observations	55,892	22,191	18,236	16,854	7,807	7,807	7,711

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1.13: Pooled Regression

	(1)	(2)	(3)	(4)	(5)	(6)
Sector = Life	0.0420 (0.20)	0.0981 (0.43)	1.443** (2.65)	1.443** (2.65)	0.325 (1.10)	0.325 (1.10)
ROA_{t-1}	-12.70* (-13.07)		-12.33* (-13.49)		-12.01* (-13.03)	
Life $\times ROA_{t-1}$	3.438 (1.35)					
ROA^*_{t-1}		-12.69* (-13.01)		-12.33* (-13.49)		-12.01* (-13.03)
Life $\times ROA^*_{t-1}$		3.263 (1.28)				
$DebtIns_{t-1}$	-0.851** (-2.90)	-0.851** (-2.90)	-0.485 (-1.44)	-0.485 (-1.44)	-0.878** (-2.99)	-0.878** (-2.99)
Life $\times DebtIns_{t-1}$			-1.886** (-2.81)	-1.886** (-2.81)		
$OpExp_{t-1}$	0.738** (2.77)	0.856** (3.24)	0.646*** (2.37)	0.786** (2.90)	1.268** (3.10)	1.404* (3.45)
Life $\times OpExp_{t-1}$					-0.953+ (-1.68)	-0.953+ (-1.68)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Macro Variables	Yes	Yes	Yes	Yes	Yes	Yes
AIC	2,141.5	2,141.7	2,136.3	2,136.3	2,140.5	2,140.5
Pseudo R2	0.104	0.104	0.107	0.107	0.105	0.105
Observations	39,743	39,743	39,743	39,743	39,743	39,743

t statistics in parentheses

+ $p < 0.1$, *** $p < 0.05$, ** $p < 0.01$, * $p < 0.001$

Chapter 2

Mergers & Acquisitions Following Regulatory Reform in the Insurance Sector

Abstract

This paper studies how the structure of the French insurance market has transformed over the past decade following the introduction of a series of regulatory reforms. We first discuss the M&A incentives given by Solvency II's standard formula, and document a predominance of “traditional” mergers—i.e., those which seek to gain economies of scale within similar lines of business. This is consistent with an absence of regulatory arbitrage. We then analyze a health-specific reform (the ANI law) and note a large wave of mergers in this sector. Using a novel data-set of 256 mergers within the French market from 2011-2019—and exploiting the fact that only a segment of the French market was exposed to this law, unlike Solvency II—we show that target companies in this business line were not associated with profitability or solvency concerns, to the contrary of mergers within other branches of activity. This result is consistent with firms anticipating the reform before the materialization of its consequences. Finally, market concentration indices across nearly all business lines remain very low, despite a large increase in M&A activity and an ever-decreasing stock of licensed undertakings in France.

1 Introduction

Between 2011 and 2019, the total number of licensed insurance undertakings present in the French market dropped from 1,074 to 695. During this period, several important regulatory reforms shook insurance markets. In January of 2016, both a European-level reform—Solvency II—and a series of French-specific health insurance reforms entered into force. Many observers believed both reforms could disproportionately affect smaller or idiosyncratic firms, and indeed a wave of mergers was observed leading up to 2016: French undertakings were the targets of over 500 acquisitions events across the aforementioned period. Further, merger activity between health specialists (the players potentially exposed to the effects of the ANI law) ceased entirely in the years following the reform's entry into force. How should these mergers be viewed in light of the regulatory context, and how has

the French insurance market evolved as a consequence?

These reforms reshaped the French insurance market in differing ways. In 2016, following approximately a decade of negotiations, Solvency II took effect across the European single market. The objectives of the reform included the introduction of a risk-based and market-consistent calculation of capital requirements for insurers, which previously was roughly proportional to the size of an undertaking. The new standard formula drastically modified the regulatory landscape across Europe, both for insurers using the standard formula and those implementing an internal model.

After the adoption of the EU Directive in 2009, some observers anticipated that the reforms would lead to a wave of M&A activity. [Stoyanova and Gründl \(2014\)](#) discussed a possible cross-border consolidation in the non-life sector for players who were large and sophisticated enough to assess the costs. Additionally, there were concerns regarding compliance costs. A report published by the European Commission following various Quantitative Impact Assessment (QIS) exercises estimated the one-off net cost of implementing Solvency II for the whole EU insurance industry to be around €3 billion to €4 billion ([European Commission \(2007\)](#)). Other observers indeed predicted a positive diversification effect of a consolidation wave stemming from the reforms (see [Carpenter \(2011\)](#)).

Concurrently with Solvency II, several transformative regulatory developments reshaped the private health insurance market in France. Importantly, this reform affected only a segment of the French insurance industry, unlike Solvency II which applied uniformly above the eligibility threshold (discussed below). In 2013, the “ANI” law (*Accord National Interprofessionnel* in French) was signed, targeting the provision of individual and collective health insurance contracts. Following the entry into force of ANI, any company of any nature must provide complementary or collective health insurance coverage to their employees. In connection with the 2013 ANI reform, a so-called “designation clause” was censored from the Social Security Code by the French Constitutional Council for its overly restrictive nature. This previous provision authorized professional organizations to impose a selected insurer (e.g., an occupation-specific mutual undertaking) to all companies in the sector. Together, these reforms widened the market and increased competition across players—putting particular pressure on firms with historically protected connections to given industries.

In the context of any regulatory reform, consolidation effects are particularly likely to manifest if the reform affects firms differently according to their size. Article 4, Section 2 of the Solvency II Directive stipulates the criteria for exclusion from scope due to size: undertakings with annual gross written premium income which does not exceed €5 million, or undertakings whose technical provisions (gross of amounts recoverable from reinsurance contracts and special purpose vehicles) does not exceed €25 million are exempt from the

regulation. One could hypothesize several consequences from this design with respect to Solvency II. First, if compliance costs have a fixed-cost component, undertakings that are small relative to market's median firm size could be asymmetrically affected given the very low eligibility threshold. These firms may therefore feel an increased incentive to merge. In this case, one would expect such mergers to occur between similar firms—i.e., firms engaging in similar lines of business—in order to more efficiently combine overhead costs and gain economies of scale. Predominance of this traditional type of merger would also be expected following the 2013 ANI health sector reforms; faced with increased competition, similar firms may seek to join forces in order to lower the overall cost per contract under management within one specific business line (individual and collective health contracts).

In the case of Solvency II, the design of the capital requirements formula could also give rise to a separate phenomenon: in addition to the question of potential compliance costs, the content of the regulation itself provides incentives for M & A activity amongst eligible firms¹ owing to the method of calculating capital requirements. Solvency II proposes a standard formula to be applied by undertakings—the Solvency Capital Requirement (SCR)—which corresponds generally to the capital required to meet obligations over the following year with a probability of 99.5% throughout different stressed scenarios. This formula breaks down risks by line of business (and other risk exposures), and subsequently provides a correlation matrix between them. Naturally, the higher the correlation between two risks, the higher the capital requirements will be.

This framework could lead to precisely the opposite type of merger; in order to take advantage of a diversification effect in the regulation, an insurer could be tempted to merge with a firm with *different* lines of insurance business or risk exposures. For instance, if the business model of Firm 1 is dominated by line of activity *A*, whose risks are considered to be only weakly correlated to those of activity *B* (in which firm 2 is present), a single merged firm would enjoy a less than proportionate increase in capital requirements when compared to the sum of Firm 1 and Firm 2's separate requirements. Analysis of this question is important from a supervisory or regulatory standpoint, as such cross-branch mergers could imply the presence of regulatory arbitrage. Understanding the motivation behind a merger can help explain subsequent outcomes on the product market. Indeed, undesirable changes in market structure (e.g., those resulting from mega-mergers seeking to consolidate a specific market) can have significant effects on the pricing and availability of products to consumers, while healthy mergers in a competitive landscape can lower costs and improve efficiency. Lastly, a wave of mergers motivated by regulatory arbitrage could have implications for the financial

¹Given the structure and scale of most European insurance markets, the vast majority of undertakings are indeed subject to the Solvency II Directive

stability of the effected industry, and inform the design of future regulatory developments.

Analysis of the greater effects of insurance regulatory reform—both the risk-based and market-consistent the Solvency II framework as well as the transformative ANI law—remains an open question in the academic literature. [Stoyanova and Gründl \(2014\)](#) discusses the incentives of Solvency II in the non-life industry (which we will develop and test below in the French market), but largely emphasizes geographically-motivated intra-European mergers. Five years after its implementation, these ideas deserve further empirical examination; indeed, foreign entities (holdings, branches, subsidiaries) compromise only 32 of the 546 total merger events identified in our unique database since 2011. Similarly, the effects of the 2013 ANI reforms have been subject to debate. [Pierre and Jusot \(2017\)](#) uses 2012 survey data to estimate that the non-coverage rate would likely fall from 5% to under 4% following the implementation of the bill, although the authors warn its welfare effects may be unevenly distributed. To the best of our knowledge, no academic studies have evaluated the market concentration effects since the law’s entry into force.

During the period of study, as outlined above, the French market has undergone several significant transformations. The objectives of this paper are therefore multiple. We firstly seek to describe the trend of mergers under the period of study in order to understand the nature of companies involved. We further analyze the temporal dynamics of market concentration indices in France, in light of the ever-reducing number of undertakings. Second, we seek to understand the links between the mergers and the aforementioned reforms. We exploit the fact that only a specific segment was exposed to the ANI law to understand how the determinants to become a target differ for this subset of firms.

Using a proprietary data-set maintained by the French Prudential Supervisory and Resolution Authority of the Bank of France initially containing 546 merger events from 2011-2019, we first show that market concentration indices for nearly all business lines remain very low in France, despite a 38% reduction in the number of licensed firms. This indicates that most targets do not hold a sufficient market share ex-ante to alter outcomes to consumers on the product market ex-post. Second, we show that 85% of mergers took place in similar business categories, consistent with a predominance of “traditional” mergers over mergers motivated by regulatory arbitrage. Lastly, we use various logistic regression specifications to show that, unlike mergers within other branches of activity, target companies underwriting over 50% of their premiums in health contracts (i.e., those firms exposed to the effects of the ANI law) were not motivated by profitability concerns leading up to the merger. This result is consistent with such firms anticipating the reform before the materialization of its consequences.

The remainder of the paper is organized as follows: Section 2 reviews the existing liter-

ature. Section 3 gives a description of the data sources and the construction of the novel data-set, and reports descriptive statistics, notably by comparing which firms engage in M&A activity with the rest of the market. Section 4 introduces the econometric strategy for our main research questions above, and discusses results. Section 5 concludes.

2 Literature Review

Our paper is situated at the intersection of several strands of literature. This brief review of academic studies is broken down along the following lines: papers analyzing the effects of financial regulation (namely, risk-based capital requirements) and those studying the effects—and determinants of—M&A activity.

2.1 Effects of Regulation

Over the last few decades, almost all developed countries have adopted risk-based regulatory regimes governing activity in the insurance sector. [Conning and Company \(1995\)](#) document how the implementation of risk-based capital (RBC) requirements in the United States property-liability insurance industry in 1994 contributed to market consolidation, as financially constrained firms lacked adequate access to capital markets to comfortably comply with the reform. A well-documented period of high-capitalization and relative stability indeed followed the adoption of these standards.²

Evaluation of the effects of Solvency II is problematic for several reasons. Certain components of the standard formula periodically face recalibration. Further, firms are heterogeneously exposed to these calibrations, since many (typically larger firms) use internal models, independent from the so-called standard formula. Most important, negotiations for the reforms began in the early 2000s, with several rounds of quantitative impact assessments (QIS) being carried before the passing of the Directive in 2009.³

One preliminary study of the initial effects of the introduction of the Solvency II reforms ([Kočović et al. \(2017\)](#)) concludes that certain key metrics, like the risk margin, prove too sensitive to interest rates, suggesting that the standard formula may be excessively conservative. [Douglas et al. \(2017\)](#) document how Solvency II may incite life insurers to “de-risk” their asset portfolios following drops in the risk-free rate (and subsequent rises in the risk-margin). Nonetheless, five years after these regulations have taken effect, evaluation of their

²Figure 1.3 from the first chapter of this thesis demonstrates a lower frequency of US insurance impairments around this time.

³See [EIOPA \(2010\)](#) for an assessment of the 5th QIS exercise, which compares own funds levels and capital requirements of European insurers under Solvency II with those under the Solveny I regime.

overall effects remains scarce in the academic literature.

2.2 Effects of M&A

Unbiased identification of the effects of mergers is notoriously problematic due to the absence of a meaningful counterfactual scenario. M&A effects using the traditional approach—measuring short-term announcement returns—appear to differ in accordance with the form of financing (Asquith et al. (1990)), the overall state of the market (see Shleifer and Vishny (2003)) or the size of the target firm (Moeller et al. (2004)). Such a metric may also often prove unreliable due to pressure from short-selling arbitrage activity (Mitchell et al. (2004)).

Overall, the longer-term effects of M&A remain an outstanding research question across many sectors of the real economy. Mergers are sometimes praised for their capacity to channel resources towards their most productivity outlets, yielding positive returns to scale. Still, many articles challenge this central idea by underscoring the pitfalls of ill-conceived mergers; those which perform poorly ex-post are often attributed to overconfident management (see Malmendier and Tate (2008) and Malmendier and Tate (2005)). A novel approach is used by one newer paper to identify the effects of mergers on firm performance. By analyzing mergers with several tender offers (merger contests), Malmendier et al. (2018) treats the “losing” firms as a counterfactual and finds that during the 3 years after the merger, losers indeed outperform winners by 24% in stock returns. Moeller et al. (2004) similarly finds negative announcement effects for acquiring firms.

The literature on M&A activity specific to the insurance sector is existent but less robust, most likely owing to non-representative nature of publicly listed insurance firms compared to the industry as a whole. Cummins et al. (1999) analyzes the relationship between mergers and acquisitions, efficiency, and scale economies for life insurance. Decomposing efficiency into several components, the authors show that mergers overall lead to increase firm efficiency over time, producing a beneficial effect overall on the industry.

Boubakri et al. (2008) study whether mergers and acquisitions in the US property-liability sector (particularly, a well-documented consolidation during the 1990s) creates or destroys value in the long term. Indeed, as mentioned above, some managers may seek to create a business empire beyond what is sustainable or rational, ultimately decreasing long-term company valuation. Here, authors estimate that M&A activity in the non-life insurance sector creates value in the long run, as measured by abnormal buy-and-hold stocks returns of acquiring firms. Further, internal corporate governance mechanisms (e.g., CEO stock participation or board independence) appear to help boost long-term productivity.

More closely related to our work is Cummins and Rubio-Misas (2019), who study the

determinants of being involved in mergers and acquisitions using data from the Spanish insurance industry from 2000 to 2012. The authors find that firms are more likely to be targets if they are less profitable and have higher premium growth rates. Composite insurers and older firms were more likely to be involved as acquirers. Further, there remains uncertainty regarding whether acquirers prefer under-performing firms (as suggested in Ly et al. (2017) in the banking sector) or instead efficient targets (as suggested by Cummins et al. (1999) in the US life insurance industry).

We now give an overview of our data by explaining our sources and providing summary statistics before introducing our econometric strategy and results in Section 4.

3 Data Overview

Our historical records of M&A activity and our firm-level financial data have both been collected the French Prudential Supervisory and Resolution Authority (ACPR) within the Bank of France. In particular, records regarding M&A activity from the Legal Affairs Department were matched with historical financial records accessed from within the Research and Risk Analysis Department. Our proprietary data-set includes, in its rawest form, 548 merger events, excluding redundant transactions; the count reduces to 359 when removing certain multi-firm events, such as a single insurer acquiring a series of different mutual insurers in a single transaction. In our regressions below, we have also dropped mergers in which one or more foreign players are involved (32 in total), as we do not dispose of any historical financial data for these firms. We additionally note that financial data from Solvency II reporting begin only in 2016; we we therefore rely on French-specific prudential filings,⁴ linking firm-level Solvency I-era data with identical data from the Solvency II era. Our econometric estimations ultimately involve 256 unique merger events amongst French firms.

Finally, all variables have been trimmed at the 0.1th and 99.9th percentiles to rid our data of noise or economically nonsensical values, particularly for financial ratios such as ROA.

3.1 Descriptive Statistics

Table 2.1 reports the number of undertakings authorized to write business in France by year, while Table 2.2 shows the number of insurers, mutual insurers and retirement or providence institutions⁵ who were involved in a merger as either an acquirer or a target throughout

⁴*Etats nationaux spécifiques*, or “ENS” in French.

⁵*Institution de prévoyance* in French.

our sample period. The total number of active undertakings has decreased monotonically from 1,129 in 2010 to 695 in 2019—a 38% decrease. While the number of insurers has fluctuated, a marked decrease can be observed for mutual insurers, whose representation has decrease from 719 in 2010 to 385 in 2019.

Figure 2.2 tabulates the frequency with which we observe each type pairing observed for these mergers (non-life acquiring life, life acquiring mutual, etc). Mutual insurers acquiring other mutual insurers accounts for 48% of M&A activity, while traditional insurers acquiring other such insurers accounts for 36%. The darker diagonal in Figure 2.2 shows us that most M&A activity in France observed over the past decades has been amongst similar insurer types. We note that this is not sufficient to conclude that firms do not seek to benefit from Solvency II's diversification affects *intra*-branch. For instance, despite being present in the same line general line of business, two non-life insurers could benefit from a merger (i.e., the merger would yield lower capital requirements compared with the sum of the two separate firms) were their risks to be diversified across the non-life module. However, for this chapter, we were unable to access the data required to measure firms' exposures and reconstruct their different SCR values. For instance, the non-life module contains three sub-modules: premium reserve, lapse, and CAT. While a premium-reserve SCR can be calculated using historical data on premiums, lapse and CAT require granular contract-level data which would make approximation impossible before 2016. Given these data-related hurdles, this question has been left for future research.

The effect of the drop on the overall market structure is largely mitigated by the size of the target firms. Figures 2.5 and 2.6 show the evolution of HHI values in the life/savings and non-life sectors respectively throughout the life of our sample. Values below 0.15 are generally considered as indicators of an unconcentrated industry; 0.15-0.25, a moderately concentrated industry; and above 0.25, a highly concentrated industry. The life sector in France, as shown in Figure 2.5, exhibits low levels of concentration. Different categories of Euro savings contracts (a popular savings tool in France) and unit-linked contracts have been grouped together given their relatively homogeneous nature; life insurers who offer savings contracts generally propose a similar mix of such products. The majority of non-life business lines are equally unconcentrated, with two important exceptions: transport and surety contracts. The latter remains above 0.3 in 2019, indicating a high degree of concentration, while the former has begun trending towards 0.10 as of 2019. In the surety industry, we notably see one key merger in 2014 which was undertaken by a one of the few dominant firms in order to acquire a peer firm operating in the same branch; around this time we indeed begin to observe a sharp spike in the HHI.

We lastly discuss the profile of firms across the market in terms of their diversification

across business lines. Perhaps owing in part to their size—which allows for the infrastructure to undertake multiple lines of business, assuming a fixed-cost barrier to entry—both acquirers and targets have more diversified activities (measured as the sum of the squared shares of the French premium categories, per observation). Figures 2.3 and 2.4 report a histogram of these measures, showing a greater business-line concentration in the non-life sector. This measure—quantitatively the same as the application above but applied *within* and not across firms—suggests a strong presence of “monoliner” firms in France.

3.2 Who Engages in M&A?

It is well documented that only a small segment of firms engage in M&A activity as an acquirer, or become implicated as a target.⁶ Tables 2.3 and 2.4 provide summary statistics by running t-tests comparing those firms which have acquired at least one other firm throughout our sample life to those who have not, as well as those who have eventually be the target of such an operation with those who have not.

Variables of interest include firm size (log of total assets), ROA (both overall and “technical”, meaning only linked to insurance activities and thus separate from investment profits), equity, loss ratio, administrative efficiency (administrative expenses relative to gross premiums written), and the share of premiums ceded to reinsurance. As discussed above, we have also created a firm-level pseudo-HHI, which measures the concentration of a given firm’s activity over a given year; a value of one would correspond to the case of a firm collecting only one category of insurance premium. We have calculated this measure for each firm-year observation, thus allowing for a firm to become more or less concentrated in its business lines from one year to another.

There are several important takeaways from these summary statistics. We observe firstly that firms which are involved in mergers, either as a target or an acquirer, are significantly larger relative to rest of the market. This is notable, given the over-representation of mutual insurers—typically smaller undertakings—among those engaging in M&A activity. Thus, despite M&A’s prevalence amongst traditionally smaller undertakings, the subset of those involved is nonetheless significantly higher than the full remainder of the industry. It should further noted that target undertakings are significantly smaller than acquirers. Depending on the motivation for the transaction, smaller players may indeed be less willing or able to dedicate the necessary resources (legal costs in particular). Additionally, many smaller firms are locally managed or historically linked to a geographic area, which may diminish the incentive to merge with an outsider. In general, the positive total asset difference for acquiring

⁶See Junni and Teerikangas (2019) for an overview of merger types and the different motives for them to take place.

firms tends to corroborate our findings below of large firms staying large, perpetuating an overall inertia in market structure.

Further, we observe acquiring firms to be more diversified across lines of business, less capitalized and slightly more profitable (as captured by the loss ratio) than firms which do not participate in the acquisition of other firms. Acquirers additionally appear very slightly more profitable, exhibiting slightly lower ROA values and significantly lower loss ratios. The characteristics of targets are also different compared to their peers. Importantly, target insurers appear to have lower equity positions over their life in the sample. This supports an *a priori* intuition that, instead of entering a restructuring plan and eventually liquidating (as observed in the US jurisdiction), European firms struggling financially tend to transfer their portfolios to healthier firms, avoiding a pure bankruptcy or liquidation procedure. Nonetheless, such an effect remains little studied in the academic literature. Overall, these two tables together lend support to the differential efficiency hypothesis, according to which acquirers are more healthier and efficient than their targets.

4 A Regulatory Reform in the Health Sector

In 2013, the ANI reform was adopted by French legislators, set to enter into force in 2016. Figure 2.7 shows the evolution through time of mergers taking place within this business line. This figure demonstrates how health firms seem to have anticipated the passage of this law—to such an extent that no M&A activity is observed after 2016, despite a continuing trend of mergers amongst other types of players. Table 2.2 also helps demonstrated how the passage of this law coincided with a considerable increase in M&A activity.

To study the effects of this law, we must analyze the health insurance firms affected by the reform. In practice, non-life, life and mutual insurers alike often underwrite business across several different business lines. To identify specialists in the health sector, we refer to the premium categories provided in the French Insurance Code (*Code des assurances*). Premium categories 20 and 21 represent, respectively, individual and collective contracts for physical or bodily damages.⁷ As a rule of thumb, we consider as “health specialists” those firms which underwrite over half of their business in the above premium categories. Other sensible ad-hoc values were tested for this threshold and produced no material difference to the results. This is predictable, given our descriptive statistics pertaining to firms’ diversification across business lines; the vast majority of insurers present in this branch either underwrite health contracts uniquely or not at all.

⁷*Dommages corporels y compris garanties accessoires aux contrats d’assurance vie individuels et collectifs* in French.

As discussed above, the ANI texts were adopted by the French legislature in 2013 and took effect in 2016. Given that these reforms implied both 1) the obligation to offer a complementary health contract to all employees and 2) granted employers the liberty to choose the provider of the contract, these reforms significantly expanded the market and amplified competition within the French jurisdiction. The economic implications of this law's design are such that certain firms not experiencing any financial difficulties today may feel the need to join forces with other similar firms to insure a continuity of their activity in anticipation of future difficulties. The three year delay between the law's adoption and its entry into force provides the industry with the opportunity to organize in exactly this manner. Below, we will evaluate how the motivations of undertakings exposed to this law appear to differ compare to undertakings whose activities were not affected by this reform.

4.1 Econometric Strategy

To test for evidence of the phenomenon described above, we rely on different logistic regression specifications.

$$p(Target_j) = \frac{e^{\alpha + \beta_j X_i}}{1 + e^{\alpha + \beta_j X_i}} \quad (2.1)$$

This equation expresses the probability that a firm of type j ($j = \text{Health, Non-Health, etc...}$) becomes acquired as a logistic function of a vector of explanatory variables, X , for each firm i in our panel. Rearranging away from an odds ratio representation, we could express the probability function as a combination of the following explanatory variables:

$$p(Target_i) = \alpha_{it} + \beta_1 \text{Log}(TotalAssets)_{it} + \beta_2 ROA_{it} + \beta_3 Equity_{it} + \eta_t + \epsilon_{it} \quad (2.2)$$

with η_t representing a year fixed effect dummy variable. The above is our baseline logistic regression specification.

4.2 Discussion of Results

In this section, we discuss how mergers amongst health insurance specialists have different determinants than mergers within the rest of the French industry. In particular, we empirically test the role of size, profitability and solvency when it comes to target firms, and compare the significance of these determinants across firm types throughout our period of study.

Tables 2.5 and 2.6 reports coefficients from two logistic regression specifications. In the first two columns (a pooled regression before the introduction of time fixed effects) we find evidence that low profitability is generally associated with M&A target firms. This confirms the analysis carried out in Cummins and Rubio-Misas (2019) on a sample of Spanish insurers from 2000 to 2012 (before the Solvency II era). Next, column 3 runs the same regression on only the subset of firms who *could have* engaged in a “health sector merger” as we have defined it in this work—i.e., those underwriting 50% or more of their premiums in this branch. Results in this column suggest that—unlike other targets (see column 4)—health specialists felt compelled to merge without experiencing profitability problems the year before the event. Table 2.6 demonstrates a similar phenomenon with equity (own funds over total assets); among the pool of non-health specialists, mergers were often associated with lower equity ratios. These results are robust to the inclusion of time fixed effects, which capture any year-specific dynamics within the industry leading up to the reform. We note that no special treatment was required for such mergers after 2016, since no such events exist in our database (further evidencing the anticipation effects across the industry irrespective of current financial health). Importantly, both subsets are of comparable size, so the significance of these findings is unlikely to be driven by a few atypical observations. Finally, as suggested by our descriptive statistics, we observe that larger firms are generally more likely to become targets than smaller firms.

We additionally introduce multiple lags to our variable of interest to better understand its temporal dynamics. Figure 2.8 plots the values and confidence intervals of different lags of a single, multiple-lag logistic regression, comparing the role profitability in the case of health insurers versus the rest of the market similarly to above. With additional lags added, this figure confirms that low profitability values were only a significant concern for non-health players—and when such problems did materialize, it was, on average, in the year directly preceding the merger. Most often, this is the last year for which prudential reporting data is available for such an undertaking.

These results imply a successful transmission of information from policymakers to the industry, as well as a unique motivation for M&A in firms most exposed to this reform. The three year grace period proved a boon to health insurers, who were able to organize themselves before the materialization of financial problems stemming from increased competition (in an already competitive, unconcentrated landscape). Such effects could indeed be aggravated for those undertakings with historically protected connections to a given industry. Further, the law importantly did not appear to have a differential effect on smaller undertakings; our evidence shows that it was larger firms who were more likely to become targets, possibly due to the increased level of expertise and resources required to engage

in M&A operations. Overall, such results imply that a grace period in the design of a competition-enhancing regulatory reform can grant firms with the necessary time to optimize their operations via an M&A channel, giving rise to mergers which (exceptionally) occur without being accompanied by low ROA values or low solvency positions.

5 Conclusion

In this article, we used a novel proprietary data-set from the French Prudential Supervisory and Resolution Authority to explore the nature of the rise in merger and acquisition activity which has been observed since 2011.

We first commented on the stability in the market structure within the French jurisdiction. In France, during the window of study (2011-2019), we observed a decrease in the number of active insurance undertakings from 1,074 to 713. Discussions had begun for the drafting of the ANI reforms in the beginning of this sample, and Quantitative Impact Assessment (QIS) exercises relating to Solvency II had already taken place before this sample window, helping fix firms' expectations and transmit information relating to the structure and impact of the reforms. Despite the consistent flow of new mergers, the decrease in the number of undertakings in the French market has had essentially no effect on market concentration measures: the market for life and savings insurers remains unconcentrated, and only two niche branches in the non-life sector exhibit higher levels of concentration. The remainder of the non-life market (like the life market) exhibits HHI values below 0.15.

We continued by assessing how the design of these two reforms may have given birth to different types of mergers with different determinants. After discussing the design of Solvency II, we documented how the vast majority of targets operate in similar business lines as their acquirers (see Figure 2.2). This evidence tends to reject the idea of firms taking advantage of the standard formula's design by seeking out dissimilar firms with the objective of jointly lowering capital requirements, in effect performing regulatory arbitrage. Instead, it lends support to the predominance of more traditional mergers, in which firms seek economies of scale within a given business line by merging with similar firms.

We then zeroed in on an additional French-specific regulatory reform—the ANI law. We exploited the fact that only a portion of the French market was exposed to this law (while the entire market, beyond a small eligibility threshold with respect to size, was exposed to Solvency II). Using different logistic regression specifications, we found evidence that the nature of health specialist mergers were different from the rest of M&A observed within the insurance industry. Specifically, our results suggest that, unlike mergers in other business lines, health mergers took place in the absence of profitability or solvency issues. Indeed,

while other M&A activity continued, activity in this branch ceased to exist as soon as the ANI law entered into force, showing an effective anticipation of insurance undertakings in advance of the law's entry into force. Further, it reinforces the absence of strategic M&A activity linked to the design of Solvency II, instead suggesting that the acquisition of most insurers coincides with financial difficulties of the target.

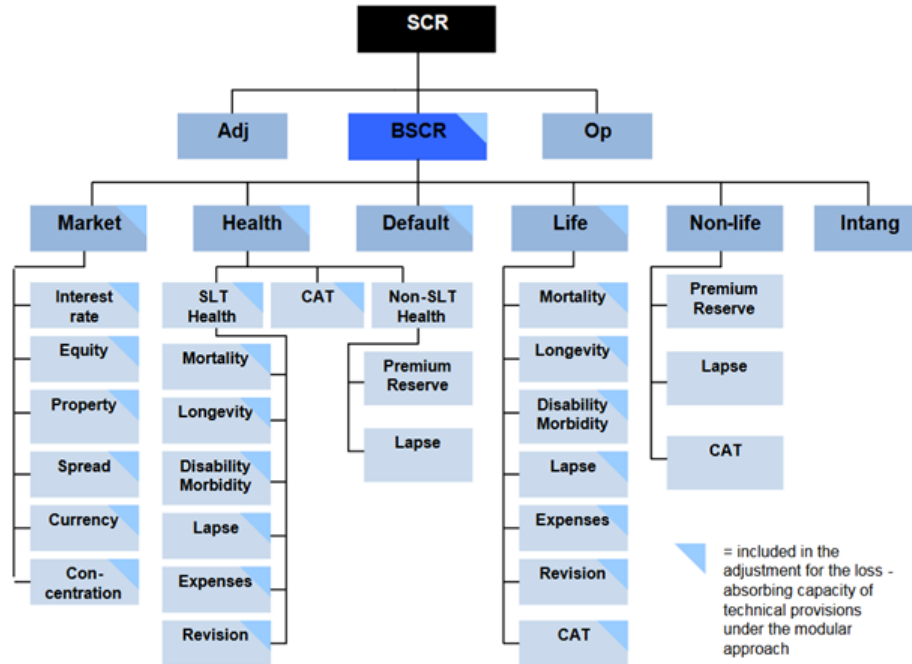
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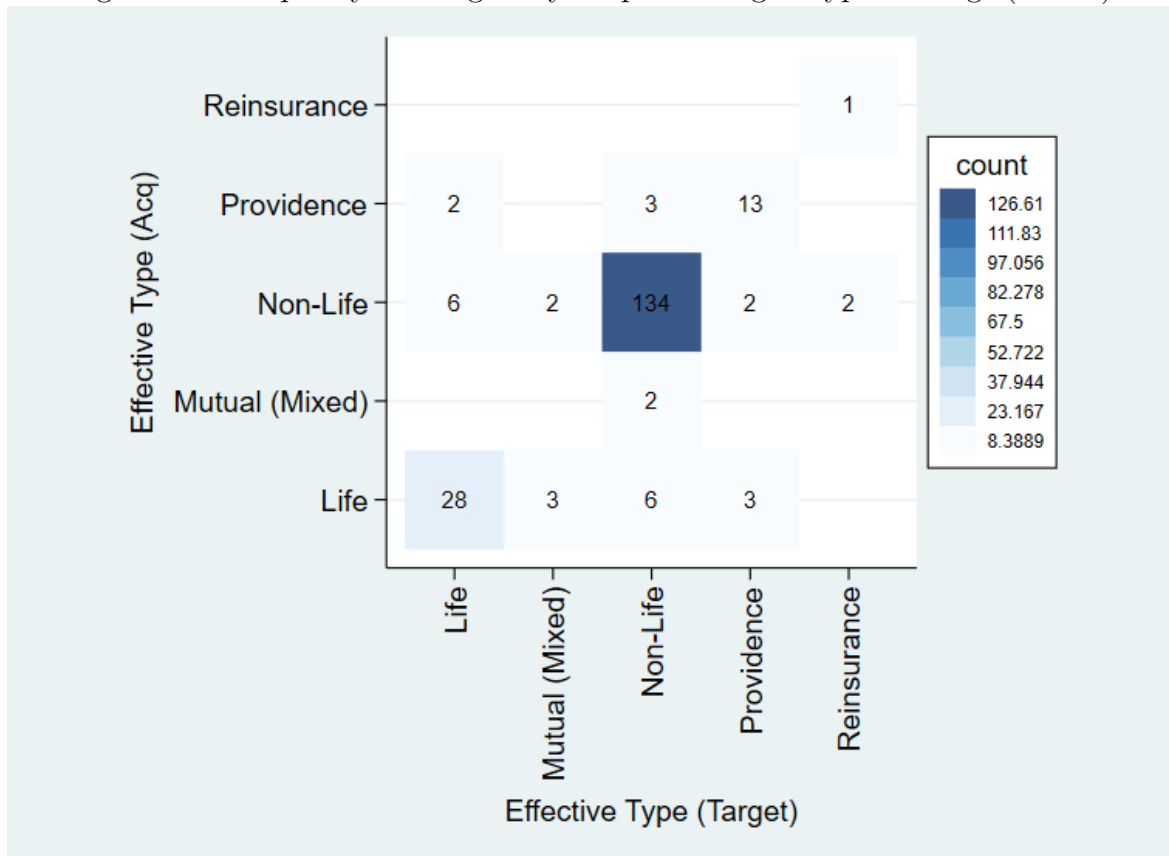
6 Figures

Figure 2.1: Standard Formula provided by Solvency II.

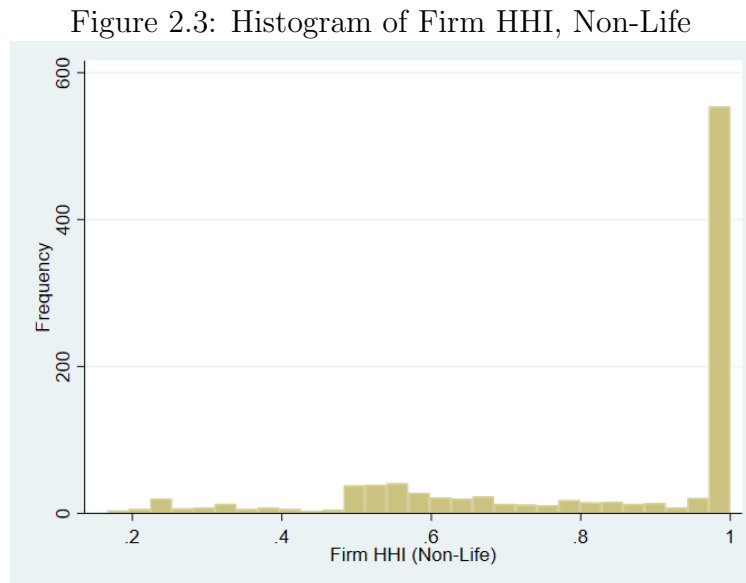


Note: A breakdown of the different risks covered by the Solvency II standard formula for calculating the Solvency Capital Requirement (SCR). The SCR is designed for an insurer to meet its financial obligations over the next 12 months in an estimated 99.5% of outcomes.

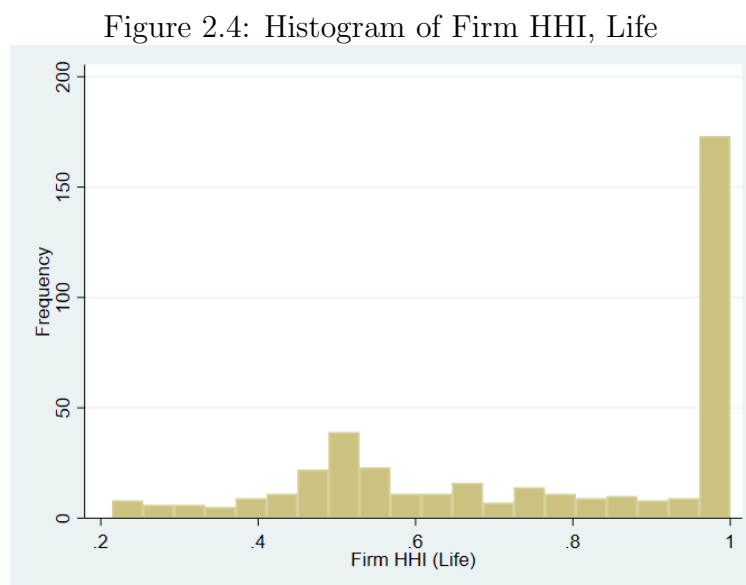
Figure 2.2: Frequency of Mergers by Acquirer-Target Type Pairings (cont'd).



Note: This figure shows the frequency with which each pairing of insurer types is observed in M&A transactions. Mergers involving mutual insurers (representing 55% of the sample, or 53% involving solely such undertakings) were re-classified into their effective type: mutual firms which underwrite more than 80% of non-life (or life) premiums are considered non-life (or life) undertakings. Firms whose business shares across these sectors fall between 20 and 80 percent of total premiums are left as "Mutual (Mixed)". By further segmenting these players, we see an even greater share of mergers (134 out of the 217 in our base) in the non-life industry.

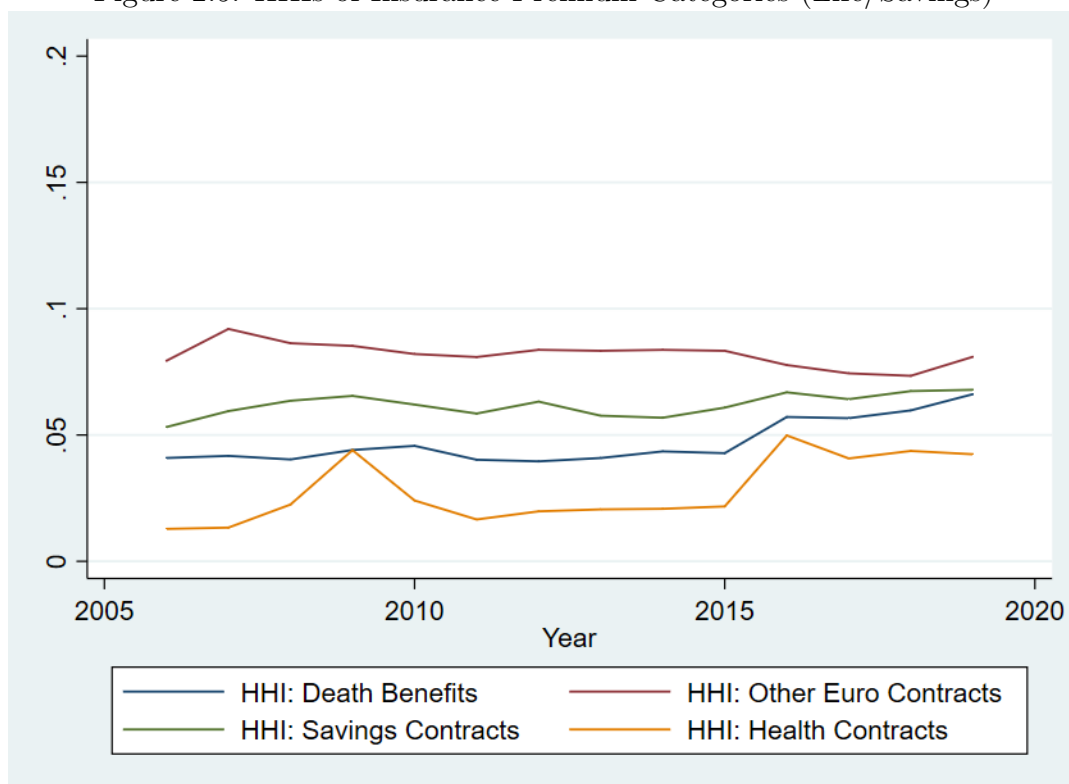


Note: This figure presents a histogram of pseudo HHI values measuring the diversification of activity *within* a given firm in the non-life industry. A value of 1 corresponds to a firm which underwrites only one type of premium contract. **Source:** Banque de France/ACPR.



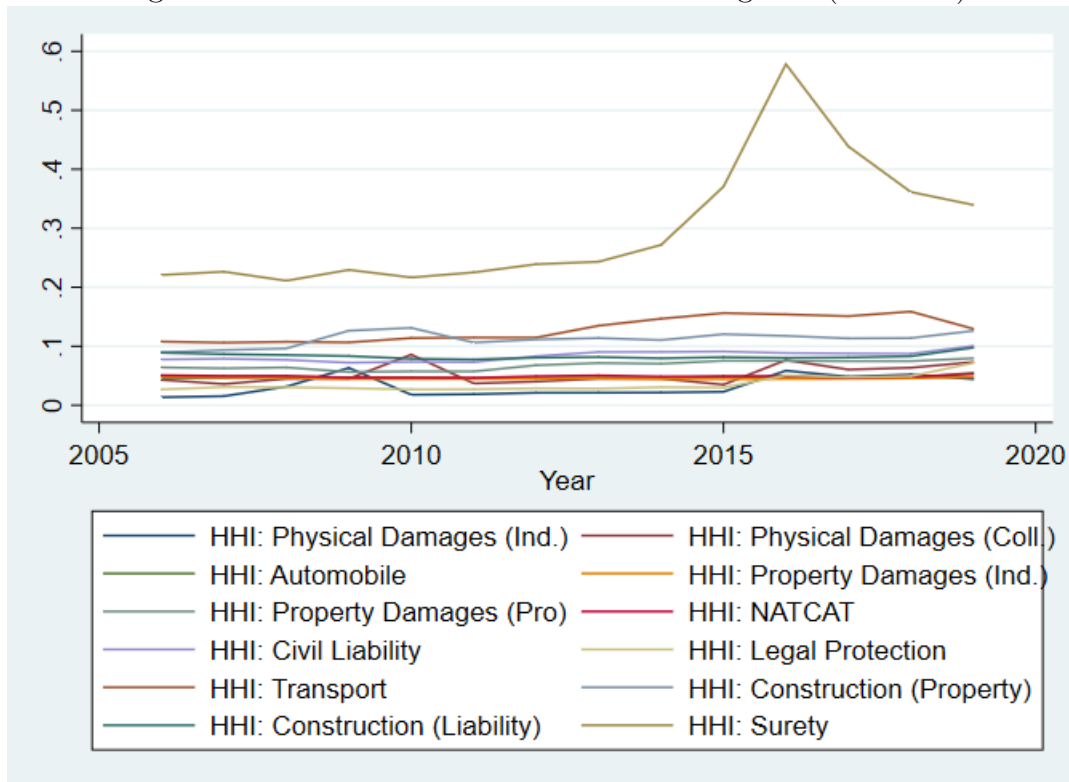
Note: This figure presents a histogram of pseudo HHI values measuring the diversification of activity *within* a given firm in the life/savings industry. A value of 1 corresponds to a firm which underwrites only one type of premium contract. **Source:** Banque de France/ACPR.

Figure 2.5: HHIs of Insurance Premium Categories (Life/Savings)



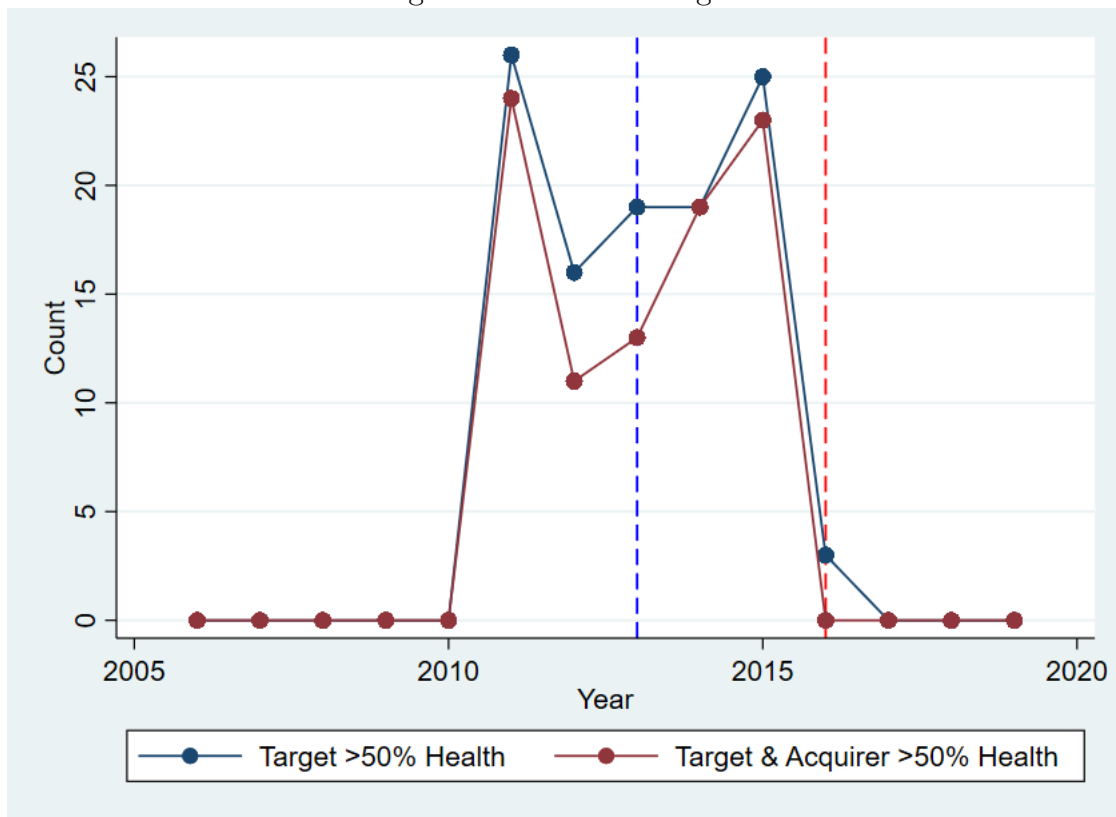
Note: This figure shows the HHI for all French regulatory insurance categories through time, from 2011-2019, for life/savings business lines. Categories 1, 2, and 8-13 are considered as Savings contracts, 3 and 6 are considered Death Benefit contracts, and 4, 5 and 7 are grouped as "Other Euro Contracts". While market concentration in the health insurance sector has increased in recent years following the aforementioned regulatory reforms, the level remains very low. Indeed, no above group ever reaches an HHI above 0.10; values below 0.15 are said to indicate an unconcentrated industry. **Source:** Banque de France/ACPR.

Figure 2.6: HHIs of Insurance Premium Categories (Non-Life)



Note: This figure shows the HHI for all French regulatory insurance categories through time, from 2011-2019, for non-life business lines. No groupings have been made, given the relatively distinct nature of each type of premium collected. Two categories stand out with values peaking over 0.25, indicating a highly concentrated industry: Transport and Surety, the latter remaining over 0.3 in 2019. **Source:** Banque de France/ACPR.

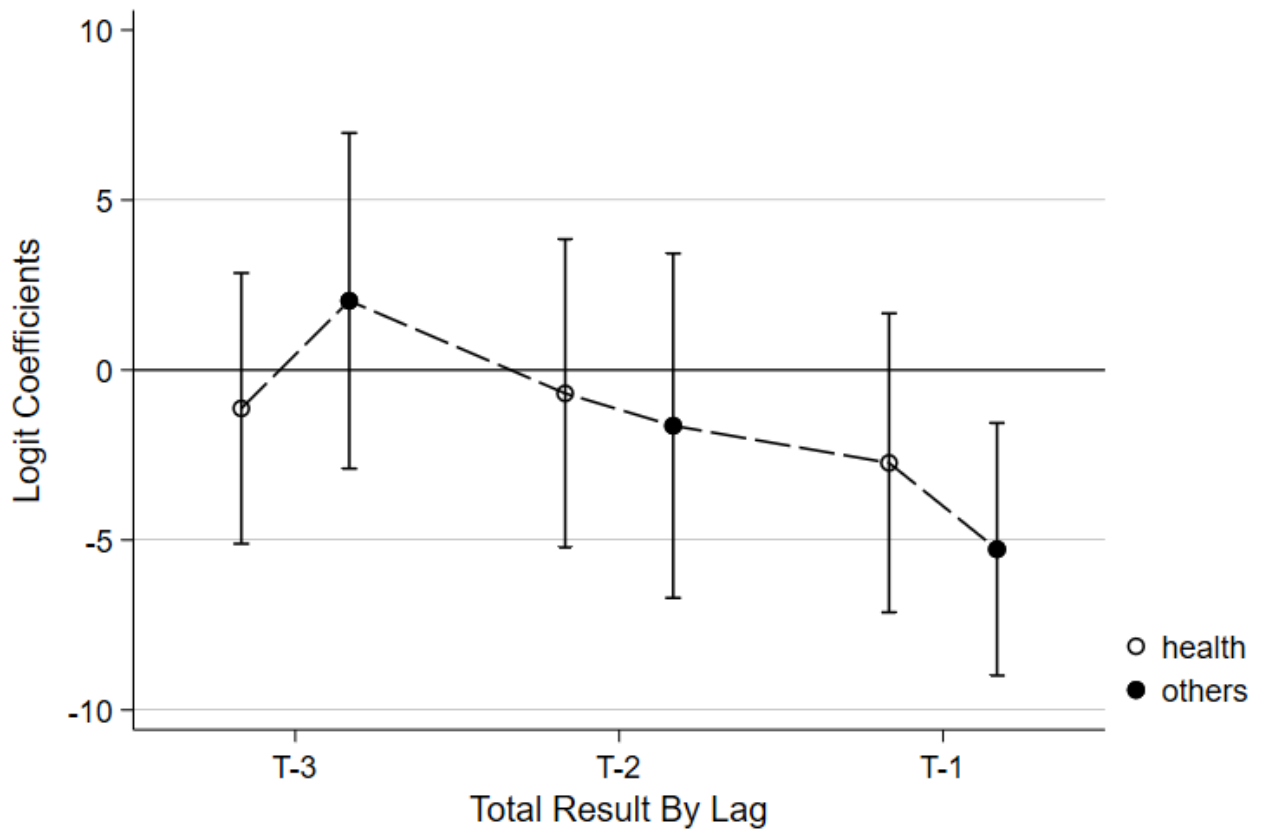
Figure 2.7: Health Mergers



Note: This figure shows the annual count of mergers in the French health sector through time. The blue line plots mergers in which only the target specialized in health premiums ($\geq 50\%$ of premiums underwritten in branches 20 and 21 of the French Insurance Code). In total, 108 M&A operations were conducted in which the target firm was a health specialist; the acquirer was also a health specialist in 90 of them. Overall this graph shows the degree to which insurers may have anticipated the various regulatory reforms which took place in 2016—the observed wave of mergers abruptly ends as the reforms enter into force in 2016.

Source: Banque de France/ACPR.

Figure 2.8: Health mergers vs others: ROA logit coefficients



Note: This figure shows multiple lags of a single logistic regression coefficients (multiple lags) for the ROA variable controlling for firm size and with a time fixed effect. No lags are significant, with the exception of the year before the merger event for non-health players. Health players appear motivated to merge by factors independent from profitability, while other undertakings appear to confirm the finding of previous literature with respect to ROA problems and target firms. **Source:** Banque de France/ACPR.

7 Tables

Table 2.1: Number of Insurance Undertakings Present in France, by Year

Type	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Insurers	329	327	318	309	299	281	273	267	263	263
Reinsurers	20	19	16	16	15	16	14	14	12	10
Foreign Branches	6	5	5	4	4	4	4	4	4	4
Insurance Undertakings	357	351	339	329	318	301	291	285	279	277
Providence Institutions	53	51	49	46	41	37	37	36	35	33
Mutual Insurers	719	672	630	599	550	488	446	420	399	385
Total Insurance Undertakings	1,129	1,074	1,018	974	909	826	774	741	713	695

Note: This table reports the number of insurance undertakings, by type, with regulatory approval to operate in France from 2010-2019. Numbers have steadily decreased, resulting in a 38% overall decrease in insurers in France over the past decade.

Table 2.2: Acquirers and Targets, By Type

Type	Acquirer	Target
<i>Insurer</i>	184	183
<i>Mutual</i>	158	141
<i>IP</i>	17	17

Note: This table shows the type of undertakings engaging in M&A activity. Mutual insurers have been particularly active, although traditional insurers are over-represented relative to their overall presence in the market.

Table 2.3: Summary Statistics, ACQ vs Non-ACQ

	(1)		(2)		(3)	
	Acquirers		Rest of Market		Difference	
	mean	sd	mean	sd	b	t
Total Assets (Log)	12.04	2.63	9.35	2.68	-2.69***	(-12.47)
Firm HHI, Life (Average)	0.68	0.23	0.78	0.22	0.10***	(3.75)
Firm HHI, Non-Life (Average)	0.63	0.23	0.83	0.22	0.20***	(9.64)
ROA (Average)	0.01	0.02	0.01	0.03	0.00*	(2.02)
Technical ROA (Average)	0.02	0.04	0.04	0.07	0.02***	(5.61)
Equity (Average)	0.39	0.27	0.53	0.27	0.14***	(6.53)
Loss Ratio, Life (Average)	0.62	0.72	0.80	1.18	0.19	(1.90)
Administrative Fees to Premiums, Life (Average)	0.13	0.14	0.13	0.21	0.01	(0.35)
Share Reinsurance Ceded, Life (Average)	0.20	0.27	0.31	0.36	0.11**	(2.88)
Loss Ratio, Non-Life (Average)	0.53	0.22	0.71	0.22	0.18***	(9.55)
Administrative Fees to Premiums, Non-Life (Average)	0.13	0.11	0.09	0.12	-0.04***	(-4.46)
Share Reinsurance Ceded, Non-Life (Average)	0.21	0.23	0.28	0.28	0.06**	(2.88)
Observations	181		1195		1376	

Note: This table of summary statistics shows a t-test of main variables comparing acquirers to the rest of the market. These firms appear larger, more diversified across lines of business, less capitalized and slightly more profitable (as captured by the loss ratio) than firms which do not engage in the acquisition of other firms.

Table 2.4: Summary Statistics, TAR vs Non-TAR

	(1)		(2)		(3)	
	Targets		Rest of Market		Difference	
	mean	sd	mean	sd	b	t
Total Assets (Log)	10.98	2.67	9.43	2.78	-1.54***	(-7.84)
Firm HHI, Life (Average)	0.69	0.22	0.78	0.22	0.09***	(3.65)
Firm HHI, Non-Life (Average)	0.76	0.23	0.82	0.23	0.06**	(2.98)
ROA (Average)	0.01	0.03	0.01	0.03	0.00	(0.61)
Technical ROA (Average)	0.03	0.05	0.04	0.07	0.01	(1.51)
Equity (Average)	0.44	0.28	0.53	0.27	0.09***	(4.41)
Loss Ratio, Life (Average)	0.63	0.53	0.80	1.21	0.18*	(2.05)
Administrative Fees to Premiums, Life (Average)	0.12	0.14	0.14	0.21	0.02	(0.88)
Share Reinsurance Ceded, Life (Average)	0.27	0.31	0.28	0.35	0.01	(0.20)
Loss Ratio, Non-Life (Average)	0.68	0.25	0.68	0.23	0.00	(0.11)
Administrative Fees to Premiums, Non-Life (Average)	0.13	0.12	0.09	0.12	-0.03***	(-3.55)
Share Reinsurance Ceded, Non-Life (Average)	0.27	0.27	0.26	0.27	-0.01	(-0.39)
Observations	232		1144		1376	

Note: This table of summary statistics shows a t-test of main variables comparing target (acquired) companies to the rest of the market. These firms, like acquirers, appear slightly larger than average (and more diversified across lines of business), although still significantly smaller than acquirers on average. Target undertakings also appear to have lower equity positions (measured by own funds relative to total assets) than their peers.

Table 2.5: Profitability and Mergers, Logistic Regression

	(1)	(2)	(3)	(4)
$\text{Log}(\text{Total}_{\text{Assets}})_{t-1}$	0.0999*** (4.64)	0.0929*** (4.10)	0.0815 (1.63)	0.116*** (3.31)
ROA_{t-1}	-5.142*** (-5.68)	-3.930*** (-3.51)	-2.408 (-1.24)	-4.515*** (-3.15)
Time FE?	No	Yes	Yes	Yes
Y-Variable	All Targets	All Targets	Health Targets	Non-Health Targets
Sample	All Firms	All Firms	Health Firms	Non-Health Firms
Pseudo R2	0.022	0.036	0.017	0.044
Observations	9,748	5,287	2,164	2,937

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the coefficients from various logistic regression specifications, focusing on ROA as an explanatory variable. Controlling for size (and gradually introducing time fixed effects), these results suggest that—unlike other targets—health specialists felt compelled to merge without having experienced profitability problems the year before the event. This suggests a successful anticipation of the effects of the health reform before its entry into force. Other mergers appear to confirm findings from previous literature (such as [Cummins and Rubio-Misas \(2019\)](#)) which indicate that target firms experience profitability concerns prior to their acquisition.

Table 2.6: Profitability and Mergers, Logistic Regression

	(1)	(2)	(3)	(4)
$\text{Log}(\text{Total}_{\text{Assets}})_{t-1}$	0.105*** (3.58)	0.0775** (2.48)	0.0942* (1.76)	0.0475 (1.07)
ROA_{t-1}	-5.246*** (-5.66)	-3.894*** (-3.36)	-2.694 (-1.36)	-4.286*** (-2.83)
Equity_{t-1}	0.0845 (0.28)	-0.211 (-0.69)	0.380 (0.72)	-1.229** (-2.37)
Time FE?	No	Yes	Yes	Yes
Y-Variable	All Targets	All Targets	Health Targets	Non-Health Targets
Sample	All Firms	All Firms	Health Firms	Non-Health Firms
Pseudo R2	0.022	0.036	0.017	0.050
Observations	9,732	5,282	2,164	2,933

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: This table reports the coefficients from various logistic regression specifications, including a solvency ratio (equity over assets) as a control variable. These results show that, on the aggregate, variation in equity (measured as own funds over total assets) was not associated with merger activity one year before the event. However, when isolating insurers exposed to the ANI reform, we see that target firms *not* exposed to this reform *do* appear to be less capitalized in comparison to other firms. This result further emphasizes that such mergers appear to have taken place before any financial difficulties occurred.

Chapter 3

Monetary Policy and Housing Loan Default in France

Abstract

The most direct channel of transmission of monetary policy to households is the modification of ECB lending and deposit facilities rates. Outstanding borrowers with adjustable rate loans face affordability conditions changes with important consequences on their financial situation. In this paper, we study the impact of monetary policy changes on housing credit default over the period 2004-2015. We use an extensive panel of French housing loans to reconstruct amortization tables over the life of each loan and compute changes in quarterly payments due to monetary policy action, later using hazard models to map changes in interest rates to default. Importantly, our data set allows the assumption of the absence of strategic default in our analysis, which isolates involuntary default in our estimates. First, we find that a 100 bp increase in quarterly payment induced by variations in the 3-month Euribor increases the probability of default by around 5%. Second, we identify employment stability as a major insurance factor against rising policy rates during contractionary monetary policy action. Finally, we provide evidence about the existence of a self-selection of riskier borrower profiles into adjustable rate loans. The concern regarding payment size on adjustable-rate loans is of heightened importance in a monetary policy context characterized by uncertainty over the timing of a rate increase following a sustained period of low or negative rates.

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1 Introduction

Expansionary monetary policy have direct effects on capital cost for new borrowers, who benefit from improved lending conditions on their housing loans. There is heterogeneity, however, regarding the extent to which existing cohorts of loans experience this channel of monetary policy pass-through. Fixed-rate loan holders see no change, while holders of adjustable rate loans face varying levels of interest payments and subsequently, income (Amudia et al. (2018)). Some borrowers with fixed rates loan may choose to refinance, although

rates need to move considerably before the decision becomes desirable, in addition to its associated costs. Also, [Mian et al. \(2013\)](#) show that high indebted households are unable to refinance to a lower rate due to their vulnerable financial situation. This prevents them to benefit from favorable credit market conditions. In this way, changes in the current policy rate asymmetrically affect holders of housing loans.

In this paper, we assess how monetary policy pass-through generates asymmetric payment size movements which affect the default probability of households' housing credit in France during the period 2004-2015. Precisely, we seek to quantify the effect of a monetary policy-driven shock to payment size on the propensity of a household to default on a loan. We also provide evidence about the role of employment stability and socioeconomic class. We use a proprietary database of around 5 million housing credit lines granted to households in the French market between 1994 and 2015. In order to measure monetary policy shocks, we reconstruct theoretical amortization tables for all credit lines in our sample, decomposing monthly payments into interest and principal components. We then use hazard model techniques to estimate the delinquency rate in a panel data framework. Importantly, unique features of our data and national jurisdiction allow us to isolate involuntary default. Further, since we exogenously observe computed credit risk ratings and additional exhaustive household features, we are able to compare peer borrower risk profiles which are unequally exposed to monetary policy shocks due to their type of interest rate (adjustable versus fixed).

In this context, our study presents several novel contributions. Firstly, this paper is, to our knowledge, the first paper to evaluate monetary policy and housing default for the French jurisdiction, and second for Europe more generally. This is particularly important in the current environment of extremely low interest rates and uncertainty regarding future variations. The ECB holds an unprecedented expansionary monetary action in the Euro zone with the aim at reaching its inflation target. This consists of record low policy rates and several unconventional tools providing high liquidity to the system. The exceptional environment of low rates may be claimed as risky for banks' profitability and raises questions about a future increase of policy rates. Our paper therefore aims to provide evidence about the impact of changes on ECB action on household solvency and their risk of default.

Second, we exploit a credit register in which strategic default is effectively absent, thus better isolating the effect of payment size on non-voluntary default. The mortgage default literature delineates between two types of housing loan defaults: those related to the ability to pay, and strategic defaults (see [Whitley et al. \(2004\)](#)). The nature of the housing loans (exposure to interest rate, required collateral, etc.) and the nature of bankruptcy laws are among the key factors which theoretically determine the prevalence of strategic default across jurisdictions [Jappelli et al. \(2013\)](#). As explained in detail in section 4 and in an IMF

on French housing prices and financial stability IMF (2013), the French context in effect suppresses the risk of strategic default due notable to the absence of non-recourse loans. The ramifications of this on our estimates are likely not trivial; in a US study, Gerardi et al. (2017) find 38% of households in default are capable of making their mortgage payments without reducing consumption. Thus, being able to disentangle non-voluntary from strategic default represents a novel opportunity compared to previous literature.

Depending on their characteristics, our study may provide insight for neighboring European countries (with otherwise similar institutions) where adjustable rate loans are more prevalent, or where financial institutions further favor their adoption. As discussed in Albertazzi et al. (2018), several European countries have a similar preference for fixed rate loans; over 85% of housing loans in Belgium, Germany and the Netherlands are fixed rate. Conversely, banks in Portugal, Spain, Austria, and to a lesser extent, Greece and Italy exhibit a tendency towards adjustable rate mortgages. Intuitively, the magnitude of our results should amplify in countries whose housing market is more exposed to the Euribor interest rate risk.

Finally, our base is exceptionally extensive for France, covering the lifespan of nearly 5 million loans. This allows us to control for a subsequent vector of household and loan characteristics in our estimations. In this way, we are able to capture the household-specific financial fragility (and other traits) and other drivers of the decision to self-select into a certain loan type. Further, we make use of an internal probability-of-default classifier which is applied uniformly across all buyers, and takes into account all of a household's financial data made available to the bank at the time of the loan application. As a consequence, we are able to compare the exposure to monetary policy action of fixed and adjustable loans while limiting the econometric selection issue, being the first European paper to do so.

Similarly to Byrne et al. (2017) in Ireland, we find that a quarterly payment increase of 100 basis points increases default probability by around 5%. Extrapolated to a concrete change of 1pp on policy rates, the resulting increment on default probability for exposed loans lies around 45%. We note that our results also hold when regressing our model only on adjustable rate loans, which is in line with US literature.¹ We additionally find, as expected, that outstanding fixed rate loans are unaffected by monetary policy action. Further, we show that employment stability represents a crucial insurance against periods of contractionary monetary policy action, reducing the default risk by around 12%. The magnitude of this result is in line with figures from Gerardi et al. (2013) on the effects of job loss. Finally, we provide evidence consistent with the idea that riskier households self-select themselves into floating rates loans, as suggested by previous literature.

This evidence is of more general importance for the design of monetary policy by cen-

¹See, e.g., Fuster and Willen (2017), Keys et al. (2014), Tracy and Wright (2012) or Elul et al. (2010).

tral banks and policy makers. On one hand, it may be desirable to lead the housing credit market structure into a “safer” zone for households which is dominated by fixed rate loans. However, this limits the transmission of monetary policy into the real economy, as only adjustable rate and new housing loans would be impacted by changes in policy rates (Ampudia et al. (2018)). In periods of contractionary monetary policy, this represents an advantage for indebted households that experience no increase in their loan payments. In expansionary periods, however, the only way to take advantage of more favorable credit conditions is through the refinancing of loans, which requires meeting a certain standard of creditworthiness. Renegotiation is crucial for those households with the most vulnerable financial situations, which are more often refused and therefore may not be able to reduce their risk of default (Mian et al. (2013), Eggertsson and Krugman (2012), Abel and Fuster (2019)). Notably, these results are particularly important in the low interest rate context, as rising interest rates could trigger default for households with existing fragility.

The remainder of the paper is organized as follows: Section 2 reviews the existing literature, section 3 gives a description of the data and the manipulations done by the authors to compute monetary policy shocks for each loan. Credit system and default evidence is documented in section 4. Section 5 details our econometric approaches. Sections 6 and 7 report results and robustness checks, while section 8 concludes.

2 Literature Review

One reason housing default has garnered so much attention in recent years is its interconnection with financial downturns, particularly the 2007-2008 Financial Crisis. Haughwout et al. (2008) and Mian and Sufi (2009) document how the expansion of housing credit, particularly subprime loans, ultimately lead to the default wave which sparked the crisis. In addition to a degradation of credit standards, households themselves undertook risky behavior by borrowing against their home equity during periods of increasing housing price. Mian and Sufi (2011) estimate home equity-based borrowing—equal to 2.8% of GDP pre-crisis—to account for at least 34% of new defaults from 2006 to 2008.

Besides falling housing prices, other changes in macroeconomic conditions can also pose a generalized risk. Mayer et al. (2009) show how increases in delinquency rates first began to rise in states which experienced elevated unemployment rates leading up to 2007.² While spells of unemployment are geographically associated with falling housing prices, borrowers

²Ohio, Michigan, and Indiana were the first states to see big increases in delinquency rates, the authors document. The default rate on subprime mortgages in these states was 14 percent at the beginning of 2007, compared with 8.5 percent rate for the nation as a whole.

who lose their job in thriving area are more likely to simply sell their house rather than default. Nevertheless, as emphasized in [Haughwout et al. \(2008\)](#), much of the increase in defaults (even at a local level) remains difficult to account for, even with rich individual level explanatory data. Most papers emphasize the importance of the loan-to-value (LTV) ratio—particularly, the case of negative equity. [Elul et al. \(2010\)](#) use LPS data on individual loans coupled with borrower-level credit bureau information from Equifax to show how liquidity shocks interact with negative equity. Following loans which originated in 2005 and 2006 until April 2009, the authors find that decreases in equity have an aggravated effect on default probability for illiquid households—i.e., those with high rates of credit-card usage. Furthermore, local unemployment shocks are found to be positively associated with default. Lastly, the authors document that the presence of a second mortgage loan is also linked with higher default risk.

Similarly, [Gerardi et al. \(2013\)](#) use a survey conducted on 8,690 households in 2009 which suggests individual unemployment to be the strongest predictor of default. The authors find that individual unemployment increases the probability of default by 5–13 percentage points, all else equal, with a sample average default rate of 3.9 percent. These results globally suggest that policies designed to promote employment would be more effective to fight mortgage default than policies which ease loan repayment standards. [Gerardi et al. \(2017\)](#) confirms this intuition, finding job loss to have an equivalent effect on the propensity to default as a 35% decline in equity, while [Hsu et al. \(2014\)](#) finds that states with generous unemployment insurance experience less mortgage delinquency.

In addition to the role of job loss, there is an ongoing debate regarding the role played by rising payments and adjustable mortgages in the 2007-2008 Financial Crisis. One side stresses the idea that difficulties meeting payments were instrumental in the bursting of the housing bubble. The predominant³ view in the aftermath of the Countrywide Financial collapse holds that rising payments on sophisticated loans triggered a wave of foreclosures. Several studies specifically address the question of changes in payment size via the interest rate channel. [Byrne et al. \(2017\)](#) study the question of monetary policy pass-through to housing loans in the Irish case by exploiting the heterogeneity across two different classes of adjustable-rate loans with different exposures to interest rate movements. Using a dataset which covers approximately 66% of the residential mortgage market, the authors show a 1% reduction in installment to be associated with a 5.8% decrease in the probability of default over the following year. They also find that negative equity has mitigated the ease in repayment due to recent low rates, implying an interaction between monetary policy and

³[Foote et al. \(2012\)](#) believe adjustable-rate mortgages played only a limited role compared with information asymmetry and irrational exuberance.

asset price shocks.

Fuster and Willen (2017) show how interest rate reductions affect repayment behavior, including for borrowers who are significantly underwater on their mortgages. The authors' estimates imply that cutting a borrower's payment in half reduces their hazard of becoming delinquent by about 55 percent, an effect approximately equivalent to lowering the borrower's combined loan-to-value ratio from 145 to 95 (holding the payment fixed). This result is in line with previous result of Elul et al. (2010), Tracy and Wright (2012) and Keys et al. (2014), which emphasize an interaction between payment shocks and housing wealth. Li et al. (2011) adopt a related but novel approach to the question by exploiting a 2005 U.S. bankruptcy reform which made it more difficult for households to discharge credit card debt. By making bankruptcy declaration more costly, fewer households could strategically declare bankruptcy for *other* debts in order to focus on their mortgage payments. The authors document rises in prime and subprime mortgage default rates of 23% and 14% respectively after the reform yet before the financial crisis.

Surprisingly, there exist only a few papers that provide consistent results on the link between payment size (particularly due to monetary policy changes) and default rates. A main reason for this is the existence of difficulties on the identification of a pure treatment effect due to the borrower selection problem. Since homeowners who demand (or resort to) a variable rate loan may exhibit a greater (and unobserved) propensity to default compared with those who hold a traditional fixed-rate loan, a group-specific estimator would experience problems of bias. Furthermore, disentangling non-voluntary payment delinquency from strategic default is a difficult task in most of developed economies due to the existence of bankruptcy rights. Moreover, this issue has been mainly studied in the US, where extensive loan level data is more easily available. Thus, evidence for European countries is almost nonexistent.

3 Data

We use proprietary data housed at the French Prudential Supervision Authority (ACPR) of the Banque de France, which contains almost 4,700,000 housing credit lines underwritten from 1994 to 2015 in France. This extensive loan-level data-set contains exhaustive information about housing loans which are secured by an insurance guarantee agreement instead of a traditional mortgage agreement. Mortgage agreements cover around 30% of total housing loans according to the ACPR (2017), while the guarantee system approximately covers the remaining two thirds. The latter involves a selection process which assures that the pool of accepted applicants represent, on the whole, a less risky segment of the market. Any

risks observed in this data-set should thus be *a fortiori* a greater cause of concern for the remainder of the market.

Credit lines are followed at the quarterly level from the quarter of origin until four possible events: 1) natural end of maturity; 2) total repayment (either credit redemption or a full principal pay-down); 3) default; or finally, 4) the end of the database visibility in the last quarter of 2015. We have three time-varying variables per credit line: outstanding principal⁴, current loan-to-value ratio (LTV) and delinquency status. Precisely, a loan is considered as being in default after 90 days of non-payment.⁵ All other variables are recorded at the time of loan formation, and therefore do not vary throughout time in our data. This includes loan information such as maturity, loan size, the type of interest rate (fixed or variable), or the downpayment rate, among others. Additionally, precise aspects of the borrower’s profile are also specified, such as annual household income, debt-to-income ratios, the number of other outstanding loans, as well as an internally calculated rating. The latter is a probability of default (PD) rating which uses credit information to rate the household’ likelihood of default over the course of the loan, and ranges for “A” to “D”.⁶ Finally, we also observe several demographic characteristics: occupation category, borrower age, marital status and postal code at loan origination.

Indeed, our database is fundamentally different from typical US cases, in that it only contains non-mortgage housing loans in which the “strategic default” dimension is much less present, as homeowners are not permitted to simply return the house to the bank. Rather than abandon the home, borrowers in our base are covered by a third-party insurance mechanism which works with borrowers to help them survive income shocks.

In addition, quarterly data on unemployment rates by *département* come from the French *Institut national de la statistique des études économiques* (INSEE), and quarterly series of Euribor index at different maturities has been gathered from the ECB’s Statistical Data Warehouse. Finally, since our register of loans was not as exhaustive towards the beginning of the sample period (1994-2003), particularly regarding adjustable loans, we decide to restrict the period of study to 2004-2015. This period exhibits considerable variation with regards to the Euribor rate, yielding an adequate window for our analysis.

⁴*Capital restant du* in French.

⁵Following the Basel III accounting conventions for default.

⁶An alternative rating is also provided: a loss-given-default (LGD) rating. This LGD rating additionally considers the size of the loan and the extent of the bank’s exposure, and ranges from Segment 1 to Segment 3.

3.1 Data Processing: Amortization Table and Interest Rate

An important limit of our original data set is the lack of direct information on interest rates and related quarterly interest payments. This breakdown of monthly payments is crucial for our identification strategy as interest rates and subsequent quarterly *interest payment* variations constitute the direct shock of monetary policy to households.

In this section, we present our strategy to leverage available information to back out a full amortization schedule of each household's payments. We use one of the available time-varying loan variables—the outstanding principal—to break down payments into principal and interest components based on a theoretical amortization table. Further, we are able to decompose the interest rate paid by adjustable rate loans into a basic Euribor component and a risk premium/spread component. For simplicity, we will first present the case of fixed rate loans as an example. Later, we will generalize the methodology to adjustable rate loans, and further detail their particularities.

To begin, we rely on the following identity of a typical amortization schedule:

$$M_t = I_t + P_t$$

M_t being the total quarterly payment in period t , which is formed by the total interest payment I_t and the total principal payment P_t . The difference on total quarterly payments ΔM over time is therefore defined as

$$\Delta M = \Delta I + \Delta P$$

where $\Delta M = M_t - M_{t-1}$. ΔP can be easily calculated since we know the outstanding principal ($Principal_t$) at each period while ΔI is unknown. Nevertheless, being a fixed rate loan schedule, we know that quarterly payments do not vary across periods (i.e., $\Delta M = 0$). Therefore, $\Delta P = -\Delta I$.

The change in the quarterly payment allocated to interest pay-down can be expressed as follows:

$$\begin{aligned} \Delta I &= Principal_t \times R - Principal_{t-1} \times R \\ &= (Principal_{t-1} - Principal_{t-1} - P_{t-1}) \times R \\ &= -P_{t-1} \times R \end{aligned}$$

where R is the quarterly interest rate. Naturally, the latter does not vary throughout time in the fixed-rate loan case.

Therefore, for loans which demonstrate a regular repayment schedule (namely, constant interest rate and quarterly payments), the quarterly interest rate is equal to the period-over-period percentage variation in the principal payments:

$$R = \frac{\Delta P}{P_{t-1}}$$

As a result, we obtain the exact interest rate R and can compute interest payments I_t (and thus total quarterly payments M_t) for each period.

Nevertheless, this methodology is *a priori* inadequate for the computation of adjustable rate payment schedules since the main assumption ($\Delta M = 0$) does not hold. By construction, the monthly debt service of adjustable rate housing loans varies across periods according to changes in their reference index. In particular, 70% of adjustable housing loans in France are referenced to the Euribor (see [ACPR \(2017\)](#)). In practice, changes in monthly payments can be updated at different frequencies (every month, 3 months, or 1 year, in general). In our data-set, we observe neither the reference index of adjustable loans nor the frequency of their adjustment. Thus, we are constrained to impose the structure of a typical case across all loans.

Our approach is the following: first, we assume all adjustable rate loans to be indexed to the 3-month Euribor. This is the most frequently used housing index according to Banque de France data sources to which authors have access. Second, we assume that loan payments are adjusted every 3 months. Finally, quarterly payment are referenced to previous quarter Euribor levels, following a conventional French loan structure. Thus, we obtain the following relationship:

$$\begin{aligned} \Delta M_t &= \text{Principal}_t \times R_t - \text{Principal}_{t-1} \times R_{t-1} + \Delta P_t \\ &= (\text{Principal}_{t-1} - P_{t-1}) \times R_t - \text{Principal}_{t-1} \times R_{t-1} + \Delta P_t \\ &= \text{Principal}_{t-1} \times \Delta R - P_{t-1} \times R_t + \Delta P_t \end{aligned}$$

Since $R_t = S + E_{t-1}$, S being the (time invariant) spread and E the 3-month Euribor, we obtain:

$$R_t = \frac{\text{Principal}_{t-1} \times \Delta E_{t-1} + \Delta P_t - \Delta M_t}{P_{t-1}} \quad (3.1)$$

Given the fact that $\Delta M_t \neq 0$ for adjustable rate loans—and not directly observed in our database—we need to rely on an alternative method to identify interest rates R_t within this group. We circumvent this issue by exploiting periods of stable monetary policy—i.e., periods during which the 3-month Euribor moves very little ($\Delta E_{t-1} \approx 0$) and we can assume that $\Delta M_t \approx 0$. As shown in [Figure 3.1](#), we have identified two main periods which respect

this criteria: 2003q3 to 2005q3, where the maximum movement is 9 basis points; and 2012q4 to 2013q4, where the maximum movement is 4 basis points. We exploit these periods to apply our above calculations, on the assumption the change in monthly payments due to Euribor variation is essentially negligible. It is worth noting that most of our sample have some period of life in our stable MP periods, thus allowing us to identify an interest rate while excluding relatively few loans from the study (1.5% of the sample).

Further, we can back out the so-called spread, or risk premium, which is constant throughout the entire lifespan of the loan. Once the spread is identified, the time-varying interest rate R_t can be proxied for every quarter using the stable interest rate periods, and interest payments I_t and total quarterly payments M_t can be calculated:

$$\begin{aligned}M_t &= I_t + P_t \\ &= \textit{Principal}_t \times R_t + P_t\end{aligned}$$

Following these manipulations, we are able to measure relative changes on quarterly payments resulting from exposure to monetary policy variations for each loan. This is what we subsequently call our monetary policy shock $MPshock_t$:

$$MPshock_t = \frac{\Delta M}{M_{t-1}}$$

A detailed example of this methodology is presented in appendix B.

3.2 Measurement Error

While both adjustable and fixed rates loans are granted in the housing market, France is one of the countries with the highest share of fixed rates on housing loans in the Euro Area. Although 97.9% of new housing loans are fixed-rate, outstanding loans exhibit a fixed-rate representation of 93.2%—a legacy of the pre-crisis trend towards adjustable rates (see [Faivre et al. \(2018\)](#)). This figure is similar in our total sample, with 10% of outstanding credit lines being floating rate loans.

The methodology we presented in the previous section perfectly computes interest rates for fixed rates loans, while in effect it approximates them for adjustable ones. While we know that monetary policy shocks are equal to zero for fixed credit schedules, the analysis presented in this paper depends on the proper measurement of changes on adjustable schemes payments. In this section, we aim to provide evidence about the accuracy of our method and the potential source of bias in posterior analysis. To this end, we simulate 780 adjustable rate loan amortization tables consisting of different loan sizes, maturities and quarters of

origin. This results in a large diversity of interest rates at origin. We use loan sizes between €100,000 and €400,000, maturities between 10 and 25 years and interest rates between 1.2% and 5.3%, which is the interest rate range of the period of study. This simulation results in 18,700 comparison points. The goal of this exercise is to apply our approximation methodology presented in the previous section to an artificial sample of data for which we have full information ex-ante, and evaluate the degree of inaccuracy of the results compared to the “true” numbers of our synthetic data in terms of interest rates.

A plot showing the true (known ex-ante) interest rate values of our synthetic data and our approximated values (i.e., the estimations given from our methodology) is shown in Figure 3.2. The true values are higher than the approximations given by our methodology. Specifically, the true rates are higher than the approximated rates in 92% of the cases. Furthermore, 95% of the deviations from the true value are between 0.07pp and -0.5pp, the median variation being -0.23pp. This implies that our methodology slightly underestimates the true interest rate. This is confirmed in our sample of study (which is different from the simulated group of loans discussed here). Figure 3.3 presents the mean interest rate at origination as published by the *Banque de France* and the mean interest rate at origination from our sample (the data used in our estimations) computed using our amortisation table reconstruction method. We observe that our approximation of interest rates follows a very similar trend than the official one, with a slightly lower level most of the time. This is in line with the results of the simulation exercise, and in line with the *a priori* intuition that our sample represents a less risky segment of the market.

Finally, we assess how the underestimation of interest rates is transmitted to the measure of monetary policy shocks. This is our main concern, since the latter is our variable of interest, while the interest rate is only the means to obtain it. Figure 3.4 presents the scatter plot between the true (simulated) and the approximated quarterly payments changes (called monetary policy shocks). We observe an almost 45 degree relationship between them, where the median value difference is €0.88. Reassuringly, 95% of our simulated sample presents a approximation error between €4 and €-4. This is considered as negligible, and proves the validity of our methodology to compute changes in quarterly payments due to variation on monetary policy rates.

Figure 3.5 shows how sensitive our methodology is to changes in interest rates for the example of loans between 100k-150k and a maturity of 15 years. The figure reports the mean computed variation of quarterly payments in the sub-sample of study and the 3-month Euribor for floating rate loans between 2004 and 2015. As the graph illustrates, quarterly payments on French ARL fall up to €460 on average compared to the previous quarter during the period of expansionary monetary policy which followed the 2007 crisis.

3.3 Weights

In addition to the concern of excluding observations using our interest rate derivation technique, a certain percentage of our loans were not “well-behaved” in other ways; i.e., they exhibited sporadic or unusual payments, were refinanced or contained other irregularities which prevented us from backing out interest rates and quarterly payment changes. We therefore exclude such cases as well, which were slightly more frequent for adjustable loans. Working only with the resulting sample could lead to additional biases in our estimates. In particular, we risk underestimating the impact of monetary policy changes.⁷

Consequently, we use a set of user-constructed loan weights for all estimations, which aim at being first and foremost representative of the type of interest rate (adjustable or fixed) and the default distribution during the period. We assume each loan to begin with a weight of 1 in the original data, since we work on true population (nearly five million loans) rather than a sample. After losing certain observations within the adjustable rate loan population, new weights are attributed to each observation. We proceed to calibrate the initial weights to re-balance our sample towards the original population distribution at each quarter. The “marginals” of the calibration (variables being calibrated) are equal to the distribution of default at each quarter and the stock of loans according to the type of interest rate, also on a per-quarter basis. The target population totals in the weight calibration are obtained from the initial true population totals for the period of study. This allows us to adjust the population at each quarter back to the original data’s distribution.

4 Default in France

The French context represents an interesting domain for research of this question for several reasons. First, housing credit is 70% comprised of non-mortgage loans. Furthermore, our database is comprised entirely of (non-mortgage) housing loans guaranteed by a third-party insurer who covers the bank against losses in case of non-payment. In this type of arrangement, the title of the asset in question is never held (and cannot be transferred to) the lending institution, which complicates the process of housing debt discharge. Second, similar to many European countries, private persons cannot benefit from non-recourse style debts. At best, borrowers who cease repayment of their loans may apply via the Bank of France to have their case considered by an over-indebtedness board.⁸ Applicants whose file is accepted may benefit from a reduction in debt owed, however at the expense of significant (and often permanent) loss of access to the banking system. Recourse to this measure is generally never

⁷See Appendix A for more detail about the potential bias.

⁸*Commission de surendettement* in French. More information available (in French) [here](#).

understood to be analogous to a strategic default. Together, these specificities imply that strategic defaults are all but absent from our database, allowing us to better understand (and better isolate) the role of changes in payment size in a world where households have few alternatives but to meet their obligations at all cost.

Additionally, a recent report by the French Prudential and Resolution Authority of the Bank of France indicated that the share of adjustable rate loans with episodes of payment delinquency has sharply risen in recent years (see Figure 3.6). This evidence goes against the mechanism of monetary policy transmission which we aim to test in this paper. This highlights the importance of multivariate analysis on the housing default question, particularly accounting for self-selection issues.

Moreover, today’s monetary policy environment represents an interesting context to study this question. 3-Month Euribor rates—the standard component of the interest rate of adjustable rate loans—have been below 1% since March 2012, and negative since May 2015. Academics and investors alike have recently debated the prospect of a rise in interest rates in the medium term. In 2019, top Federal Reserve officials signaled no need for further interest rate decreases in the United States⁹, while the Bank of England indicated that a growth rate of 1.5% may be sufficient to justify a rate increase¹⁰. Recent ECB research suggests that, across countries, adjustable rate loans become more popular in the presence of higher inflation, smaller correlation between unemployment and the short-term interest rate, higher financial literacy of households and where MBS-related regulation is looser (see [Albertazzi et al. \(2018\)](#)).

4.1 Descriptive Statistics

In Tables 3.1 and 3.2, we conduct simple t-tests on key variables which we later use in our regressions. Table 3.1 compares loans which have defaulted with those which have never defaulted across the entirety of the sample, while Table 3.2 compares adjustable and fixed rate loans. We firstly observe that defaulting loans exhibit significantly higher values for our credit rating metric, indicating higher risk. Additionally, defaulting loans have an average down-payment rate of 10% and slightly over one other outstanding loan on average, compared to 19% and 0.8 respectively for healthy loans. These figures are consistent with the substantially higher annual interest rate that we observe for defaulting borrowers at origination. We also note that loans which default are longer in duration than those which do not, and that defaulters have significantly higher LTV ratios at origination. We see two important takeaways from this fact. The first is the reality that a longer lifespan of a loan

⁹Derby (2019).

¹⁰Inman (2019).

increases the exposure period and the opportunities to default. The second interpretation—coupled with the fact that loans tend to default early in the lifespan—is that longer loans stay in high LTV-value ranges for longer, which can discourage borrowers as they may feel less at stake in the event of delinquency.

Regarding the type of interest rate, we note that both types of borrowers present similar interest rates levels at origin (Table 3.2). Nevertheless, we observe several differences which suggest that adjustable rate borrowers have riskier profiles than fixed rate ones. They present higher LTV ratios, with substantially lower initial down-payment (13% vs 19% on average). Borrowers with floating loans ask for substantially larger loans in size (24500€ larger on average) with significantly lower volume of down-payment at origin (3500€ lower savings on average). Although adjustable rate borrowers present a 13% higher annual income than fixed rate ones, their loan size is 20% higher on average. This results in a significantly larger debt-to-income ratio. Previous research shows that higher income households are more prone to choose adjustable schedules since they have higher income risk bearing capacity (Albertazzi et al. (2018), Brueckner and Follain (1988)). Moreover, ARL households have a higher number of other outstanding debts at origin compared to FRL. These are standard characteristics found on the literature for households selecting ARL. According to Campbell and Cocco (2003), households with binding borrowing constraints are more likely to choose the loan with the lower interest rate in order to reduce their initial payments and indebtedness ratio. Intuitively, loans schedules which offer the lowest level of interest rate are adjustable rate loans. This pattern is particularly true in periods of higher rates and house prices. One reason is that the slightly lower interest rate at origin may makes the difference between respecting banking financial ratios and criteria to be granted with a loan or being refused (Paiella and Pozzolo (2007)). Moreover, financial literacy has been proved to play an important role in understanding the risk of the two different contracts¹¹ given households characteristics (see Fornero et al. (2011)). This evidence highlights the riskier profile of ARL borrowers and explains their substantially higher rating level on average. Thus, controlling for an exhaustive set of variables which captures the difference on the risk profile of the borrower is important to asses delinquency events. The existence of self-selection into adjustable rate loans schedules by riskier borrower profiles could importantly bias the estimation of the nature of the interest rates impact on default probability.

Additional insights are provided by Figures 3.7, 3.8 and 3.9. These graphs plot non-parametric hazard functions—i.e., the instantaneous probability of default at each moment through time, conditional on never having previously defaulted—broken down by different buckets or categories. Firstly, figure 3.7 confirms our plain intuition that adjustable rate loans

¹¹Unfortunately, this is not a variable that is available in our data set.

are more likely to default throughout the entirety of their lives in the sample. Independently of the fact that we evaluate a period of time with both contractionary and expansionary monetary policy action, we observe floating loans defaulting more than fixed rate loans. This is importantly related to the self-selection of riskier profiles into adjustable rate loans and highlights the importance of accounting for this bias in order to be able to compare peer loans.

Secondly, Figure 3.8 plots the default probability by credit default rating category and shows the striking discriminatory ability of internal credit ratings. As expected, default probability increases with the rating grade, indicating that risk *D* loans have almost twice higher probabilities of payment delinquency than rate *C*, while *A* borrowers hardly ever default at any time in the sample. This breakdown is also striking in Table 3.3, which shows a cross-tabulation of defaults by rating class. While the average default rate of the sample is 0.85%, borrowers rated as *D* have an average default rate of 4.36%, and *A* borrowers only 0.32%. The proper accuracy of the rating representing borrowers risk at origination is the main hypothesis of our identification strategy and helps us assuming that we account for any prior risk factor that would explain self-selection into adjustable rate loans. This is a very important variable in our analysis. As previously mentioned, the relevance of LTV ratios is confirmed in Figure 3.9. Default is related with high Loan-to-Value ratios, this is when borrowers are most leveraged, having the lowest equity stake in the property.

Finally, we can see a common mode across all figures around the 3-4 year mark (and falling monotonically thereafter), indicating that loans are most likely to default early on (when LTV ratios are high). The probability of default after 10 years (having never defaulted previously) is half that of 5 years. This evidence may be explained by low equity households having more difficulties to refinance due to their tight financial situation. This may also be consistent with borrowers losing hope if financial difficulties have persisted from the beginning of the loan life.

5 Econometric Approach

The identification of the effect of payment size on housing loans default has often been presented in the literature as a difficult issue for two main reasons. The first factor is the presence of certain time-varying macroeconomic conditions which have important consequences on the evolution of interest rates; interest rates rarely exhibit variations without changes in underlying business cycles. Second, the cross-sectional heterogeneity in interest rates (and thus monthly payments) may be simply explained by a selection bias; a borrower's risk of default at the loan origin explains the interest rate level of the loan, which in turn

explains a significant part of payment heterogeneity and default at a given moment in time. Furthermore, one expects households to self-select into fixed or adjustable rates according to their characteristics, many of which may be unobservable. For example, borrowers with poor credit history may self-select away from traditional products in which more risk is borne by the lenders. Less risk-averse households with higher financial constraints may also choose floating-rate loans more often in order to reduce their initial payments and indebtedness ratio. As a consequence, we may observe floating loans to default more simply because such households represent particular profiles. Together, these factors present a reverse-causality issue, rendering pure cross-section and time-series analysis on interest rates to identify the link between payment size and default problematic (see [Fuster and Willen \(2017\)](#) for more discussion). Statistically consistent analysis would therefore require the means to control for household selection effects and macroeconomic factors affecting loans granted conditions.

In order to overcome this difficulty initially pointed out by [Yezer et al. \(1994\)](#), our preferred empirical design would compare two borrowers with the same risk profile at origination and equivalent loan combinations except for the degree of exposure to monetary policy changes. In other words, we would follow identical borrowers (and loans) that differ solely on the nature of the interest rate: floating versus fixed rate. The borrower with a floating loan would be exposed to changes on monthly payments due to monetary policy, while the one with a fixed rate would be unaffected. Such an approach is possible thanks to our set of exhaustive control variables on borrowers' profiles and loan characteristics at origination.

Exploiting our rich loan- and household-level data, we thus include an extensive set of loan and borrower characteristics at origin as controls. We notably leverage the existence of a credit rating score, which is applied uniformly to households regardless of their loan choice and will allow for the comparison of peer borrowers. We assume all residual differences in risk profile across borrowers, unexplained by our controls, to be captured by this rating, an approach employed notably by [Jones and Sirmans \(2015\)](#). These data capture for example, the wealth holdings of borrowers and their portfolio structure, which importantly play a role in the capacity to absorb income shocks with rate fluctuations. We thus assume that the choice between adjustable and fixed rate type is mostly explained by exogenous factors other than the risk profile, such as risk aversion level or financial literacy. This is our best attempt to remedy the issue besides an experiment in which borrowers are randomly assigned with different monthly payments.

We propose the following discrete time proportional hazard model panel estimation fol-

lowing previous literature (Fuster and Willen (2017), Foote et al. (2012)):

$$Default_{it} = \beta_0 + \beta_1 MPshock_{it-1} + \beta_2 LTV_{it-1} + \beta_3 Controls_{i0} + \beta_5 Unemp_{dt-1} + \alpha_t + \alpha_d + \epsilon_{it} \quad (3.2)$$

where we model the risk of default of loan i at time t as a function of two main variables of interest: changes on quarterly payments due to a monetary policy shock $MPshock_{it-1}$ (as computed in section 3.1) and the housing equity position of the household over time LTV_{it-1} . The latter represents the outstanding principal over the current housing asset value at each period, and is presented in different categories in order to allow for non linear effects. Unlike Fuster and Willen (2017), we are able to directly measure the direct impact of ECB policy action on household quarterly payments.

Furthermore, we control for an exhaustive vector of loan and borrower specific characteristics at origination $Controls_{i0}$ which includes: loan maturity, loan-to-value, type of housing project (main residence, secondary residence or investment), household income, the number of total outstanding debts of the household and age of the borrowers. Accounting for loan-level information is important because housing loans are differentiated goods priced according to their attributes. For example, average interest rate of new housing loans varies in loan maturity and loan size. Banks allocate higher rates to longer loans in order to protect themselves from future uncertainty, since their visibility of long-term events decreases in length. Further, we expect banks to charge higher interest rates as the amount of the exposure to exogenous risks increases (loan size). Typically, loans with higher LTV ratios at origin represent riskier loans for the bank, often translating into higher borrowing costs. Certain loans which exhibit ratios above 1 (implying, e.g., a component of the loan intended for a renovation project) are considered particularly vulnerable. Similarly, investment projects may be perceived as riskier or more speculative than residential ones. Information regarding indebtedness and affordability, as well as the credit history of the borrower, are additional pieces of information used by lenders to assess borrower risk. As previously explained, in addition to previous controls, including a direct objective measure of risk (credit rating) exogenously evaluated by a third-party insurer institution ensures the control of selection effects, as explained by Jones and Sirmans (2015).

Department-specific unemployment changes U_{dt-1} are also included to understand the role of the job loss on loan delinquency. Time and department fixed effects are present in our econometric specifications to help control for all geographic heterogeneity (besides unemployment) and macroeconomic quarter-year-specific changes. These dummies help remove any structural differences in level of our variables, such as a lending premium present throughout a relatively disadvantaged region, a local trend in housing prices or household

income, or the overall health of the credit market in a region of the country. This facilitates the assumption of exogenous monetary policy (driven at European level), which is assumed to be uncorrelated to regional economic dynamics. Including time fixed effects is important to account for time-varying economic conditions which have important consequences on the evolution of interest rates. Unlike in previous literature, both are possible here thanks to our unique measure of monetary policy shock at the loan level.

Lastly, discrete time proportional hazard models are conceived to explain transitions from one state to another (regular state to default, in our case). This class of models is particularly attractive as it is capable of handling so-called right-censored observations—in our case, loans which exit the panel (and thus live beyond our ability to monitor them) due to attrition or other reasons prior to experiencing default (see Allison (1982) for an in-depth discussion on this technique and its applications in the social sciences). Since a loan’s life may stop at some point previous to 2015 for various reasons explained in section 3, we work with an unbalanced panel of data for our baseline specification. Additional tests are proposed in the robustness section 7.

6 Results and Discussion

Table 3.4 reports the results of a simplified version of Equation 3.2, in which we first compare default probability between the two groups of interest: fixed and floating rate loans. Columns 2 to 4 provide results for a set of different fixed effects and controls. For simplicity in the interpretation of our results, we will focus on the effect of the variables of interest; the rest of the coefficients are generally in line with previous literature. The table begins with a simple loan type dummy showing that floating loans are 29% more likely to default on average during the period of study, and that higher LTV buckets are indeed riskier, as expected. Households starting a credit line with an underwater equity position ($LTV > 1$) present 3 times higher probabilities of default than those with a loan lower than 60% the value of the housing asset (column 2). We then capture the monetary policy context by creating dummies representing periods of expansionary and contractionary monetary policy, later including our set of risk profile controls. We define a “contractionary” period as a quarter which experienced a rise in the 3-months Euribor for at least two consecutive quarters.

As expected, for identical borrower profile and loan characteristics, floating loans default around 30% less in periods of expansionary monetary policy (with decreasing interest rates) compared to peer fixed loans. Entering a period of increasing rates (contractionary monetary policy) raises the default probability by 13% for ARL on average, while it has no significant impact for twin FRL. Further, in column 4, we note that including the set of controls

inverts the coefficient of our rate type dummy (ADJ). This confirms the existence of self-selection into variable rate loans of riskier profiles, and shows the importance of accounting for selection effects. Our contractionary monetary policy dummy (and its interaction with adjustable-rate loans) remains unchanged in sign. This result reinforces the validity of our identification strategy.

Table 3.5 reports the main results of estimating equation 3.2 including different fixed effects and controls. Our main result, as observed in column 3, is that a 1 percentage point shock on quarterly payments last quarter increases the default probability by 5%. This effect is significant at 0.1%. We give an idea of the economic magnitude of this result in section 6.1. The nature of our data and the french regulation allows us to claim that this result represents non-voluntary defaults. This implies that rising policy rates during periods of ECB contractionary action has important consequences for households financial fragility, which are not explained by own propensity to default for riskier households nor strategic default. Borrowers of adjustable rate housing loans are exposed to changes on interest rates and importantly react to those variations. This can be an important advantage during periods of falling rates, but can become a substantial threat at the time of contractionary monetary policy.

Contracting a loan with higher LTV levels at origination (or, alternatively, lower down-payment rates) is associated with much higher default risk during the credit life. Taking out a loan for more than the value of the home increases default risk by almost 40%, according to our benchmark specification in column 3. Moreover, the housing equity position at the moment of nonpayment plays a major role in explaining default. Looking to current LTV buckets, we see a non-linear effect through time. In particular, reaching the last 20% of outstanding debt reduces the probability of delinquency by almost half compared to households in an underwater position. One possible explanation for this phenomenon is that more heavily indebted households encounter harsher financing conditions if they seek to take out an additional loan or to refinance their original loan. Households with lower LTV ratios therefore may default less often due to the relative ease at which they can access new or better financing following an idiosyncratic shock. Furthermore, they may be willing to undertake additional efforts at finding means to ensure the continuity of payments since they are closer to the natural end of maturity.

The most discriminant control variable is the internal rating: each risk tranche monotonically increases the probability of default, while the riskiest risk tranche is over 10 times more likely to default, all else equal. This suggests the existence of additional borrower profile features or soft information which are invisible for us, but required by lenders to evaluate risk profile. As expected, higher household income helps survival in the sample, while other

outstanding debts burden a household’s ability to repay, confirming an intuition provided by Li et al. (2011). Primary residences are the ones defaulting the most, while rental properties are less likely to default than primary residences and secondary residences, providing evidence against reckless or speculative investment in this type of asset. This finding is further in line with the fact that housing investment projects are evaluated by banks according to their associated rental revenues, which remain an additional guarantee.¹² Additionally, one may expect more financially sophisticated borrowers with greater positions of wealth to make housing investments.

The estimation of Equation 3.2 is replicated using a classic linear panel model with individual fixed effects and weights. The objective is to provide an alternative estimation which fully accounts for time-invariant latent characteristics of individuals which could explain self-selection (e.g., risk aversion or education). Results are presented in the last column of Table 3.8, and are equivalent to previous ones in terms of changes in quarterly payments, loan to value rates and as controls.

6.1 Policy Rates and Default

The benchmark estimation presented in the previous section finds a significant relationship between ongoing households’ housing loan payment schedules and default probability in France. Nevertheless, this connection is driven by changes in interest rates to which loan amortisation tables are indexed, as explained in section 3.1. In this section, we provide evidence about the more direct link between policy rates themselves and payment schedules. This additional exercise is important because the variation in the policy rate has not been modelled to directly explain default in our main specifications presented previously, therefore precluding the precise quantification of a concrete monetary policy change on the probability of default. This exercise is therefore useful to clarify the transmission channel and highlight its magnitude in order to analyze the effect that a change on policy rates would have on delinquency events.

As follows, we study variations in quarterly payments, which themselves depend on the policy rate (the 3-month Euribor).¹³ We therefore choose to estimate a linear relationship between changes in the 3-month Euribor and the subsequent changes to the quarterly loan payments for floating loans in our sample as follows:

$$MPshock_{it} = \lambda_0 + \lambda_1 \Delta R_{it} + \lambda_2 Principal_{it} + v_{it} \quad (3.3)$$

¹²French banks deduct around 50% of expected rents from total debt payments in order to compute affordability ratios.

¹³ $\Delta M = Principal_{t-1} \times \Delta R - P_{t-1} \times R_t + \Delta P$

While $MPshock_{it}$ represents the quarterly payment change between t and $t - 1$ of loan i , ΔR_{it} is the change on interest rate of the loan schedule with the interest rate defined as $R_t = S + E_{t-1}$, with S being the (time invariant) spread and E the 3-month Euribor. By definition, any change on interest rates is driven by changes in policy rates. Importantly, the effect of a given policy rate change will have heterogeneous results on households payments depending on the total outstanding principal of each loan in t . In order to account for the possible disparities in loans structure over time, which may be explained by our sample construction, we therefore include *Principal* as a control variable. We ultimately regress different estimations for 4 different groups corresponding to quantiles of interest rates R during the period of study in order to be capture different monetary policy environments.

The results of the estimation of Equation 3.3 for these four different quantiles of interest rate *levels* are summarized in Figure 3.10. The plots represent the slope of each estimation assuming a linear effect of policy rates changes on quarterly payments growth. As expected, the higher the interest rate environment (quantile 4), the smaller the relative impact of a given change on interest rates. Overall, a 100 basis point change on interest rates leads to a quarterly payment growth between 7% and 9% on average.

Then, we use these magnitudes and test their impact on default from our baseline specification presented in column three of Table 3.5. Precisely, we compute the predicted margins (i.e $Pr(\hat{Default})$) for different levels of $MPshock$ (containing the range of rates obtained in the previous step) holding all other explanatory variables at their sample means (except for fixed effect dummies, which are kept at their observed values). This exercise provides us with the predicted default rate in our sample for different assumptions of monetary policy payment shocks between -10% and 10%. Results are presented in Figure 3.11.

Intuitively, we obtain higher delinquency rates for larger changes on quarterly payments. The probability of default increases from $\approx 0.025\%$ —when there is no change on quarterly payment—to $\approx 0.04\%$ when quarterly payment grows 10pp. This small magnitude of these results in absolute terms is explained by the enormous size of our control sample (fixed rate loans); indeed, loans with fixed payment schedules over their life represent around 90% of our sample and are not impacted by changes in policy rates. This fact may in part explain why the French delinquency rate is one of the lowest of the European Union in general (1.4% in France vs 2% on average in European countries in 2017 according to the [ACPR \(2017\)](#)). Moreover, we study a segment of the French market known to be less risky (loans which are insured through a guarantee mechanism), which may further explain the resulting smaller unconditional probability of default provided in this exercise.

For reference, we found that a 100 basis point rise on policy rates increases the quarterly payments $MPshock$ in 9% on average on an environment of low interest rates in the first

step of this section. Subsequently, according to our baseline results presented in the previous section, a rise of 9pp in the monetary policy shock to quarterly payment size can be translated into an increase of default probabilities by around 45%, all else equal. This impact on default probability is significant in relative magnitude. Nevertheless, it merits emphasising that the large relative increase should be understood in conjunction with the small absolute probabilities presented in Figure 3.11, since changes in policy rates only concern a small part of the spectrum of ongoing loans (adjustable rate loans).

The evidence provided in this section suggests that changes in the 3-month Euribor may have substantial consequences for households linked to variable payment schemes. However, observed increases in the average overall delinquency rates may be small, given the strong prevalence of fixed rate loans in France, making the detection of such defaults difficult to detect. This is important since exposed households who choose adjustable rate loans are known to represent a riskier segment of the population and to be particularly vulnerable ex-ante. By quantifying the impact of a change on policy rates in loan quarterly payments, we provide some elements about the magnitude of the monetary policy transmission onto the housing sector according to different policy paths. While this exercise cannot be interpreted as predictive for future events regarding monetary policy, they may be useful and provide some insight on the direction of the consequences that may be expected. This can be particularly relevant for countries and financial systems with an important share of variable rate loans, openly exposed to policy changes.

6.2 Heterogeneous Effects of Monetary Policy

The results of our baseline specification are strong in magnitude and significance. In this section, we test whether the identified effects are heterogeneously distributed across the population according to certain borrower characteristics. Several interactions between monetary policy shock and different loan and borrower characteristics are therefore presented in Table 3.6.

First, we test for a possible interaction between our monetary policy shock and LTV levels France (column 1), as suggested in US literature (e.g., Gerardi et al. (2017)). We thus combine current LTV ratios and our measure of quarterly payments changes due to policy action. We find no significant difference regarding the impact of monetary policy shocks on housing loans delinquency depending on the level of equity. Households do, however, default twice as much when LTV ratios are in their highest level; although their equity position does not affect the way they face and absorb changes on interest rates. Here, we nonetheless avoid associating this variable with strategic defaults for several reasons. Firstly, these loans

are not mortgages, so borrowers cannot abandon their loans by surrendering their home to banks. Further, the French jurisdiction differs from the American context regarding the ability to engage in this practice, as well as regarding personal bankruptcy procedures, as explained above. Lastly, high (and, especially, positive) LTV values are a necessary but not sufficient condition for default; most voluntary defaults occur with high LTV values, although not all high LTV defaults correspond to such cases.

Overall, our results are in line with the idea that declaring bankruptcy for housing debt holders is not a choice but a forced result of a bad financial situation. Indeed, as discussed above, since the forgiveness of housing accumulated debts in France requires a long administrative process with very strict criteria and an element of discretion regarding the granting of bankruptcy status, we expect little effect of this phenomenon on our estimates. Additionally, the fact that households more frequently default early in the life of the loan (when equity is lower), regardless of changes in monthly payment shocks may imply that affordability is a problem that is carried over from the beginning of the credit.

Importantly, we would like to assess how households react to quarterly payments changes depending on their income level. Unfortunately, we do not observe income evolution in our data and providing proper estimates about this question represents a difficult task. Nevertheless, we tested a certain number of specifications which include an interaction term between income¹⁴ at origin and our variable of interest (*MPshock*), with the aim at assuming that the level of income at origination is similar during the entire period of study. This strategy does not allow the analysis of changes in income, but only how relative changes on loan payments affect the default probability depending on income level. First, we estimate our benchmark model with our interaction of interest during the first 7 years of the loan life.¹⁵ This alternative is quite imperfect because it is known that income at the beginning of the working life highly evolve, creating estimation bias which depends on age. Second, we restricted the sample to individuals who contracted the loan between 35 and 45 years old and we observe their credit life only during this age window.¹⁶ This alternative relies on the income literature showing that during this period of the life-cycle income stabilizes (Mazumder (2005)). According to the literature, observing income at one of these points is representative of the average income around the 40's. Although more precise than the first approach, this alternative also present weaknesses. Some individuals are only observed

¹⁴We test both income as continuous variable and in quantiles.

¹⁵Example: an individual aged 32 years old at origination till her 39 years old, and an individual aged 50 at loan origination till her 57 years old.

¹⁶Example: an individual aged 37 at loan origination till her 45 years old, and an individual aged 40 at loan origination till her 45 years old. Individuals aged less than 35 or more than 45 at loan origination are excluded.

during a couple of years, and depending on whether you are 37 or 43 the income bias may be still different. Finally, we adapt the last approach by restricting the sample to individuals who contracted a loan between 35 and 38 years old, and we follow them till their 45. This reduced the bias associated to the age of start and relies on the income stability hypotheses. Nevertheless, none of these alternatives give significant results on the existence of heterogeneous effects of quarterly payment changes depending on income levels. Thus, we are unable to provide evidence regarding this issue and we believe further research must be done, particularly using more adequate time-varying income data.

We additionally sought to test several hypotheses relative to the role of job loss in housing loan default. Namely, we wanted to understand how unemployment shocks (at the department level) interact with payment size shocks, and for which segment of the population these effects play the most pronounced role. To test the latter idea, we chose the socioeconomic and employment categories which we assume to be the most exposed to sectorial shocks. We create a “Vulnerable” dummy which is equal to 1 for the worker/employee¹⁷ level employment status (as opposed to management-level employees). Table 3.7 reports how such households make up 24.7% of our sample, yet account for 30.7% of defaults. Results are presented in columns 2 to 4, the latter representing the most developed specification.

Interestingly, we find that simple payment shocks do not have a significant impact on the delinquency probability of the less vulnerable employment segment, while belonging to the more vulnerable segment of households increases default probability by 3.9% after a 100 basis points monetary policy shock. Nevertheless, facing a payment variation and an unemployment shock both at the same time seems to play a role for both groups of interest. The same monetary policy shock increases their default probability by 1.2% if it is combined with a change on unemployment of the same magnitude. Nevertheless, this additional effect is slightly lower for vulnerable households, who already accumulate the initial effect of the monetary policy shock. As a consequence, vulnerable households’ likelihood of non-payment increases by 4.5% if both events take place simultaneously. Furthermore, we find a specific effect for “vulnerable” socioeconomic category which defaults 7.5% more on average compared to the non-vulnerable households during the period of study. Finally, unemployment seems to have no impact on default probability for any of the population groups on its own. This is not surprising, as France provides a very robust unemployment subsidy system, which further is consistent with the idea presented by Hsu et al. (2014) that states with generous unemployment insurance experience less mortgage delinquency.

These results are of particular importance because they signal the high exposure of households to employment stability, which can increase the impact of a monetary policy shock (on

¹⁷ *Employé et ouvrier* INSEE category

default probability) by 7.5% compared to households who have been through the same shock from an stable employment position. The magnitude of this result is in line with the those of Gerardi et al. (2013), who find that unemployment shocks increases the probability of default by 5-13pp. This evidence shows the existence of a heterogeneous impact of monetary policy across the population.

7 Robustness

7.1 Non-random Renegotiation

A second issue to take into account is the non-randomness of early exit (or, alternatively, the unbalanced nature) of our panel. As explained, we observe credit lines until the end of their lives (whether they default or not), or alternatively until the moment of total repayment due to a renegotiation or other reason (e.g. inheritance). The latter represents the end of the credit line and is explained by the original wealth levels of the households, which are accounted for using household characteristics at origination, the LTV and the credit rating. Nevertheless, households renegotiating their loans will close their current credit line and start a new one, which cannot be traced or precisely identified in the data. Thus, we stop observing a loan's evolution at the time of a refinancing. This is potentially problematic, since households leaving the sample due to renegotiation are expected to exhibit more creditworthiness than those staying, who may have attempted to refinance but were refused (see Mian et al. (2013) for a detailed discussion). As suggested by previous literature, the role of house prices on the creditworthiness of households is not considered crucial in the French case, due to the low share of mortgage loans within the mass of housing credit.¹⁸ More generally, our data-set contains exclusively non-mortgage loans, although other characteristics explaining households' creditworthiness over time are unobservable, and as a result, the potential for a self-selection problem remains.

For this reason, we seek to test our baseline specification against alternative setups which serve to remedy these concerns. First, we restrict the sample to the first 7 years of life, assuming a smaller likelihood for creditworthiness to change in the years immediately after the initial loan was granted (column 1 of Table 3.8). Second, we restrict the sample to only loans in their first 7 years of life with a loan maturity longer or equal to 20 years, which is the most common loan maturity in France (column 2, Table 3.8). By restricting the length of the loan we exclude shorter loans which are more likely to be refinanced. Finally, we exclude fixed rate loans from our sample and we focus on a period of time in which renegotiation

¹⁸Only, 30% of new loans according to ACPR (2017).

incentives are at their lowest for floating loans (column 3, Table 3.8). The latter are the years of expansionary monetary policy. Fixed rate loans are excluded because their renegotiation patterns are more complicated; they depend on the level of interest rates at each time compared to the one at origination, and the number of years left to fully repay the loan balance. Hence, we make the assumption that households with floating schedules have no incentive to renegotiate during periods of falling rates, as long as policy rates expectations follow the same trend.

On the other hand, holders of floating loans would like to renegotiate if they expect interest rates to rise. As an additional test (seeking to exclude periods of high loan renegotiations), we run our baseline specification only on adjustable loans and excluding such periods of increasing interest rates. While expectations dynamics are more complicated than this, we consider this approach a plausible simplified version which is supported by the forward guidance policy of the ECB. These tests are presented in Table 3.8. The magnitude and significance of our main result remains virtually unchanged in the first two columns, and decreases to 2% taking a sample of only adjustable rate loans during expansionary periods. This result is significant only at the 10% confidence interval range. Further, by restricting our sample, we see that the effect of negative equity is much more severe for adjustable-rate loans; our Current LTV > 1 dummy jumps to its highest value in column 3. This result suggests that the initial span of credit lines may have been affected by a selected attrition in which households with better financial situations left the observed sample under a different timing compared to remaining loans. The estimation of these alternatives allows us to test the robustness of our specification in a more balanced setting. The results are shown to be equivalent, suggesting no relevance on the unbalanced structure of the data at the origin of our sample of loans.

8 Conclusion

In this paper, we investigate the effect of monetary policy on the propensity of a household to involuntarily default on their housing loan. Using a confidential Banque de France dataset of around 5 million housing loans, we reconstruct full amortization tables for each loan, computing monetary policy driven changes on quarterly payments. We conclude that a 100 basis points variation in quarterly payment due to a change policy rate increases the probability of default by 5%. Extrapolated to a concrete change of 1pp on policy rates, the resulting increase on default probability for exposed loans lies around 45%. Further, due to jurisdictional differences between France and other countries regarding bankruptcy laws (as well as the absence of mortgage-style loans in our data), we are able to isolate purely

involuntary defaults in our analysis. This desirable trait of our data helps to identify (and control for) the determinants of default driven by financial distress, as opposed to voluntary default from solvent households, which have different dynamics and causes. Conducting an estimation on a database which contains both types may serve to obfuscate the true factors explaining loan delinquency.

Additionally, as in previous literature, we identify a strong role of employment stability against default risk during periods of contractionary monetary policy engaged by the ECB. Finally, we provide ample evidence consistent with the existence of a self-selection of riskier borrowers into floating rate loans schedules, as suggested in the literature. Our results are robust to a set of alternate specifications which serve to remedy potential selection concerns. While the magnitude of our coefficient decreases considerable in some cases, there remains a positive and significant effect of the growth rate monetary policy shocks.

This evidence is of more crucial importance for policy makers, especially in a period where many observers predict interest rates to rise in the short term as a result of the long-lasting expansionary monetary policy, which has put on the spot financial institutions position. Increasing policy rates in the years to come may have substantial negative effects on households' financial situations, leading to a wave of default events, although a total welfare analysis of such a scenario is left for future research.

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9 Figures

Figure 3.1: Stable Monetary Policy Periods.

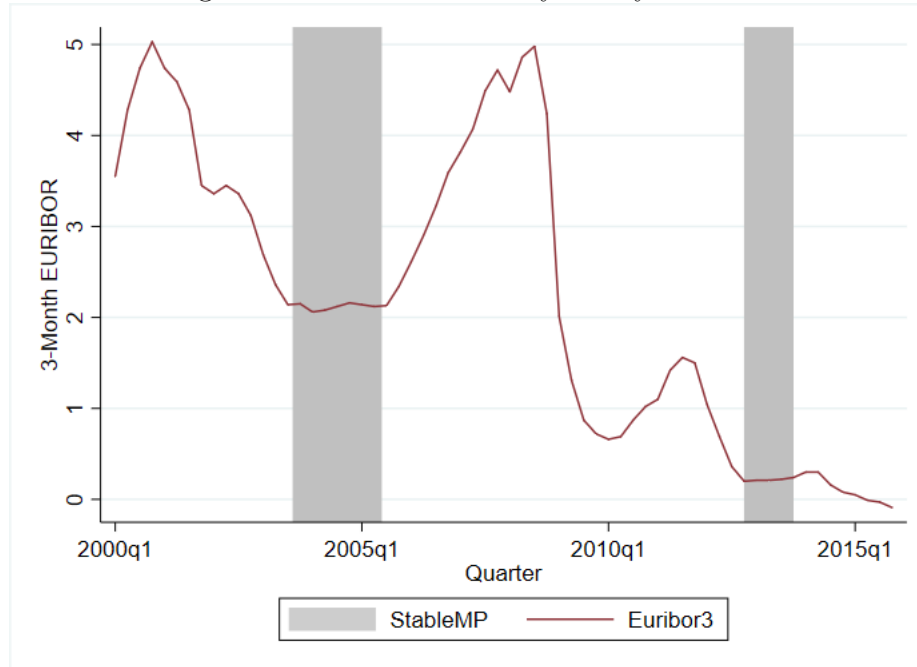


Figure 3.2: True vs Approximated Interest Rate (Simulated Loans)

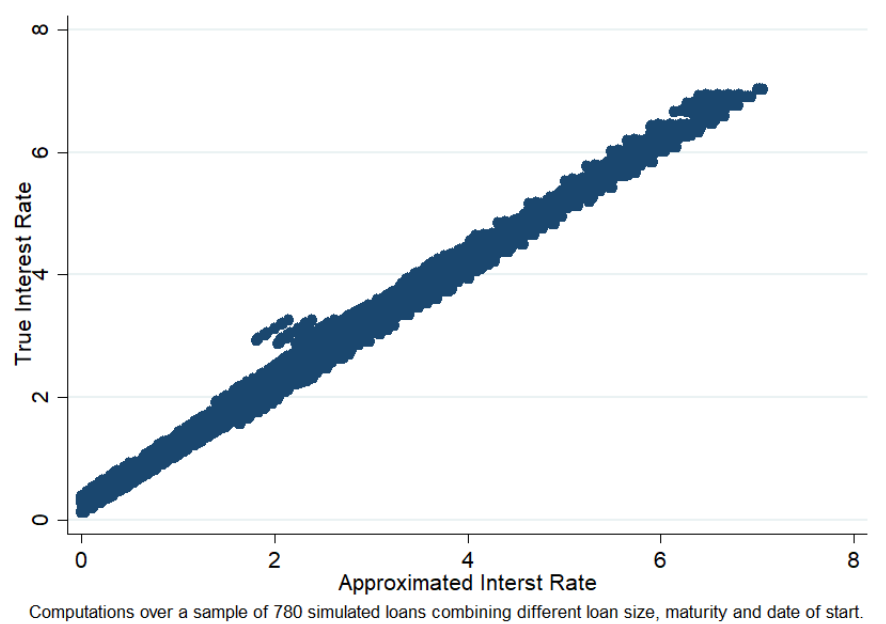


Figure 3.3: Average Interest Rate at Origination, by Quarter

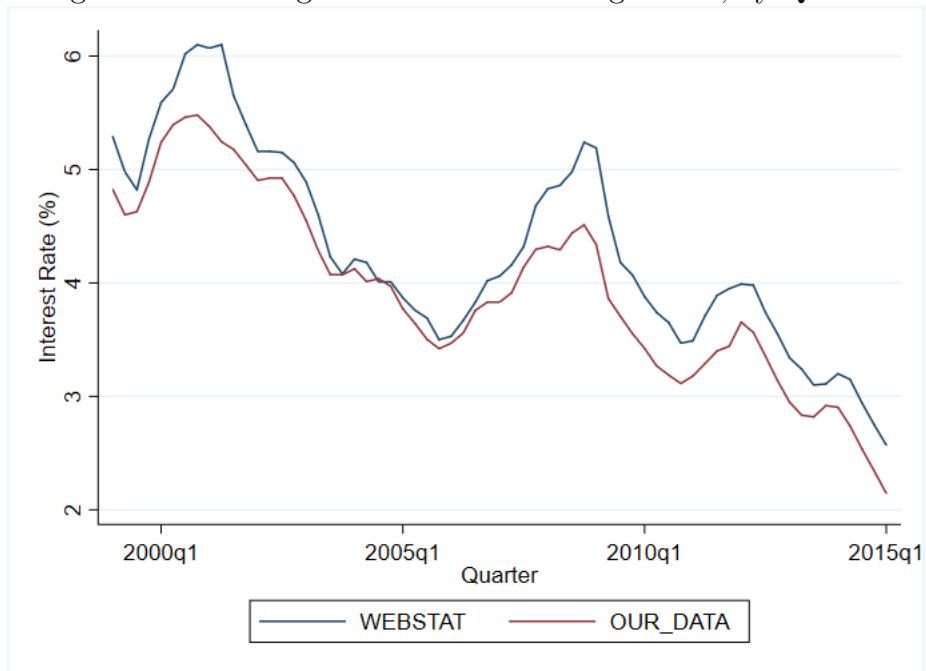


Figure 3.4: True vs Approximated Monetary Policy Shock (Simulated Loans)

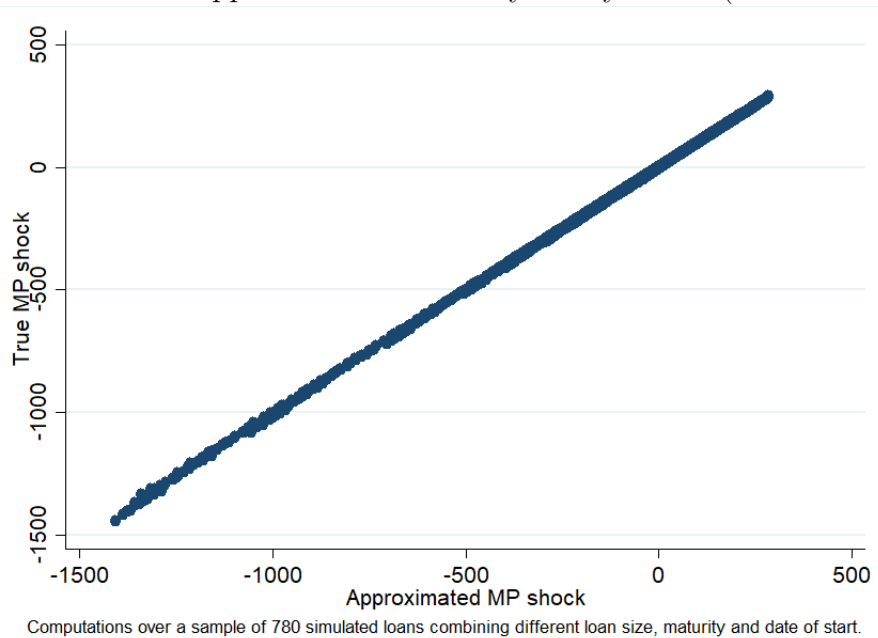


Figure 3.5: Average Change on Quarterly Payments (Adjustable Rate Loans)

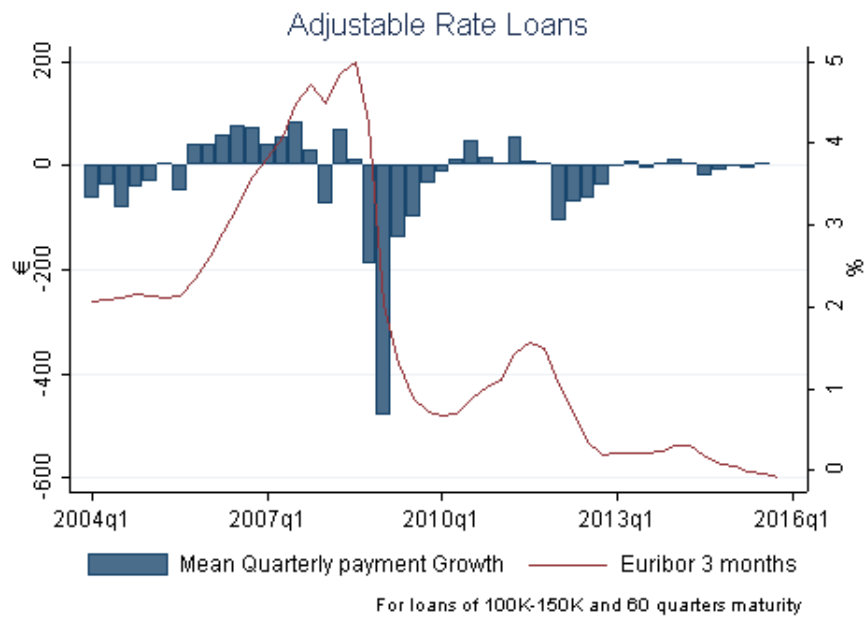


Figure 3.6: Share of Doubtful Payment Outstanding Loans, by Loan Type

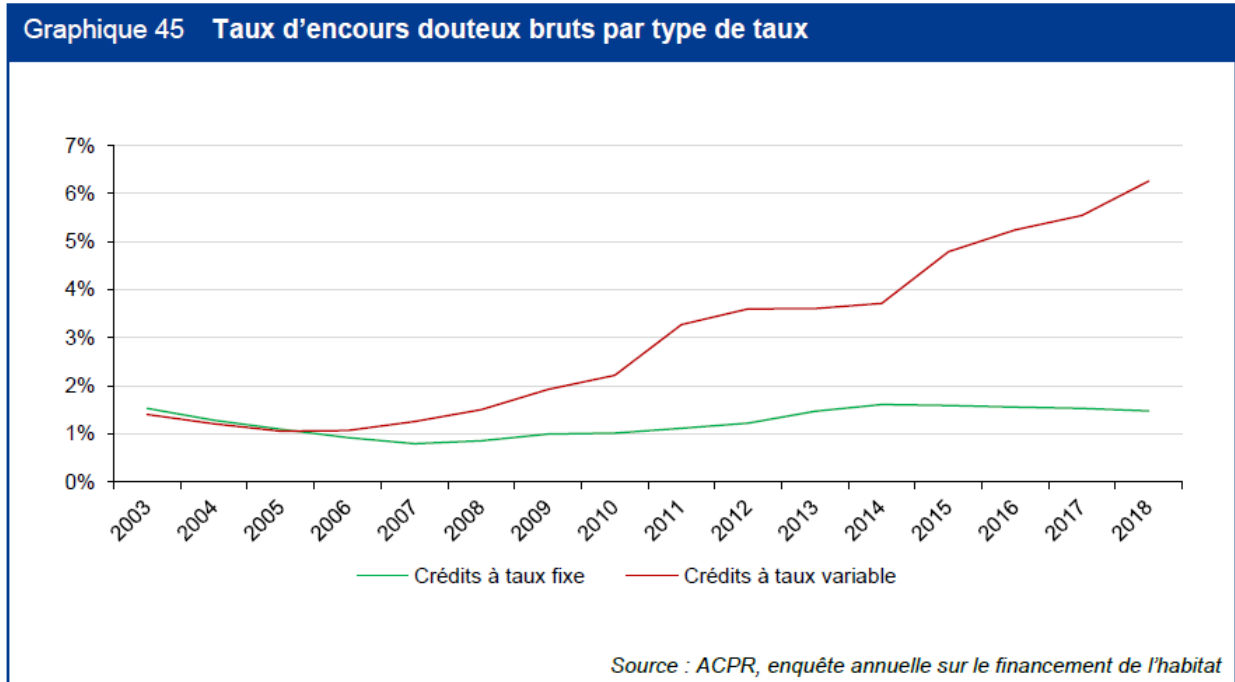


Figure 3.7: Hazard Function, by Loan Type

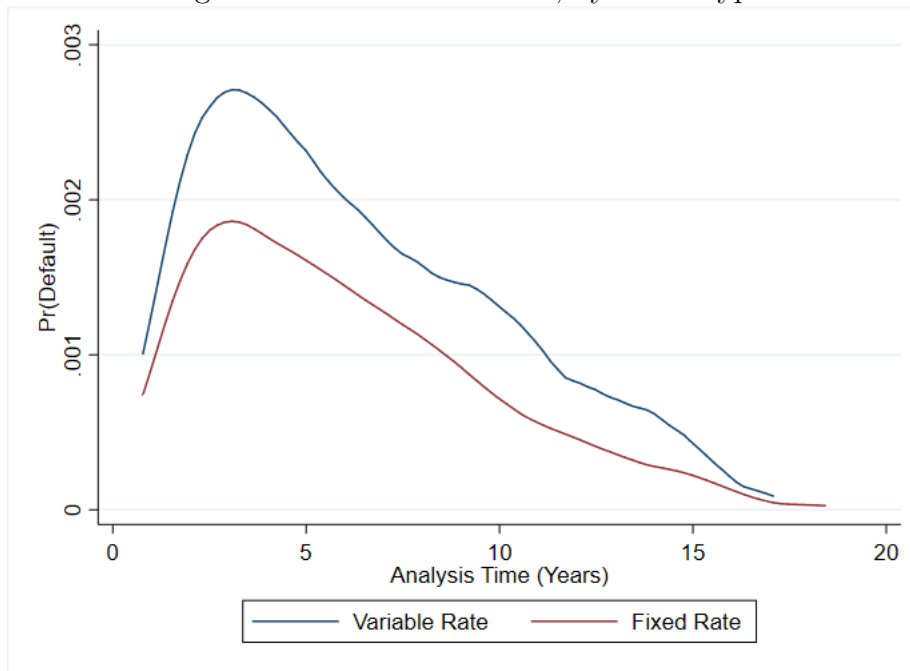


Figure 3.8: Hazard Function, by Probability-of-Default Rating

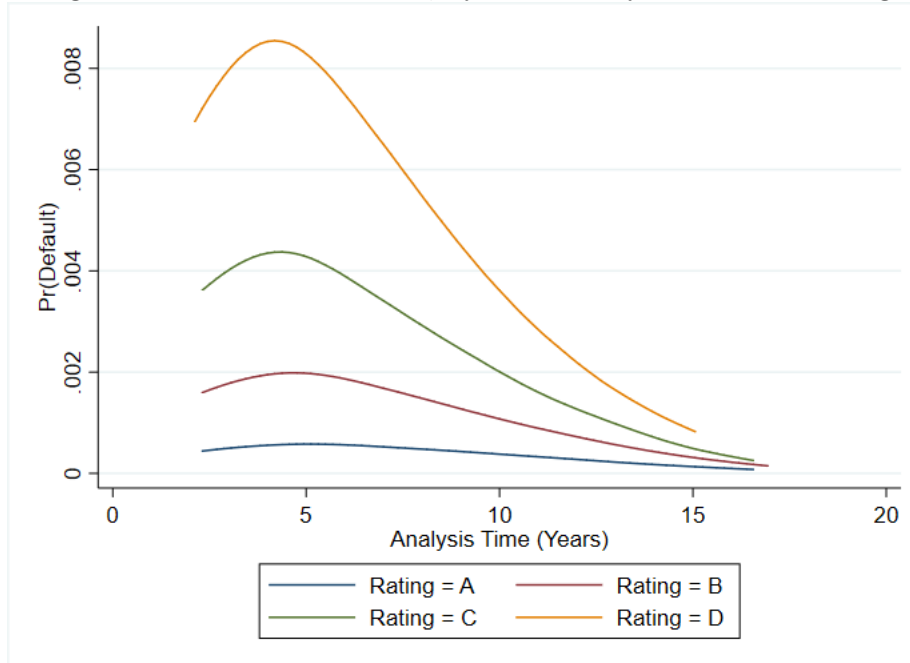


Figure 3.9: Hazard Function, by LTV Tranche

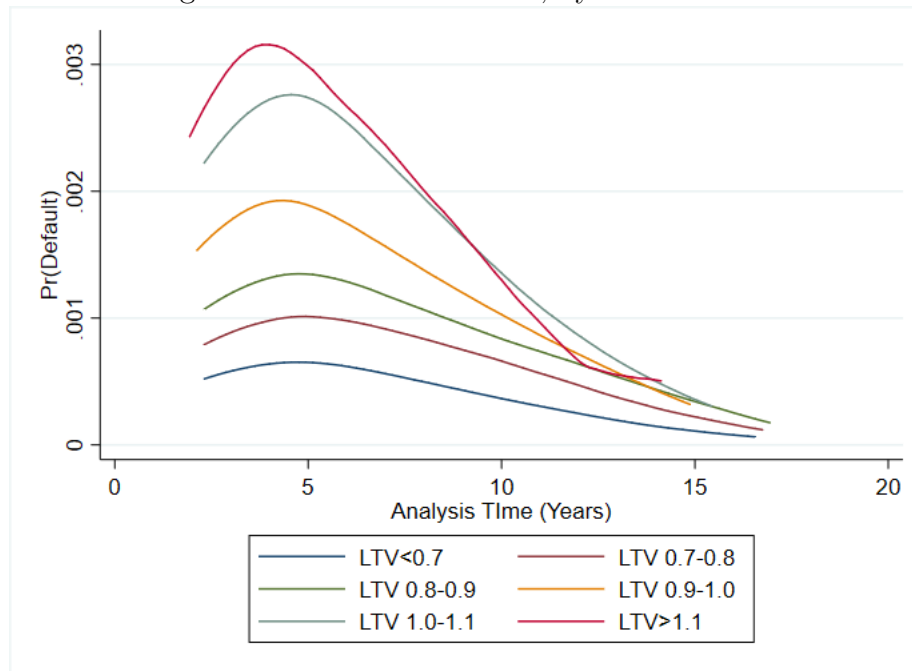


Figure 3.10: Predicted Quarterly Payment Growth (%), by 3-month Euribor Shocks

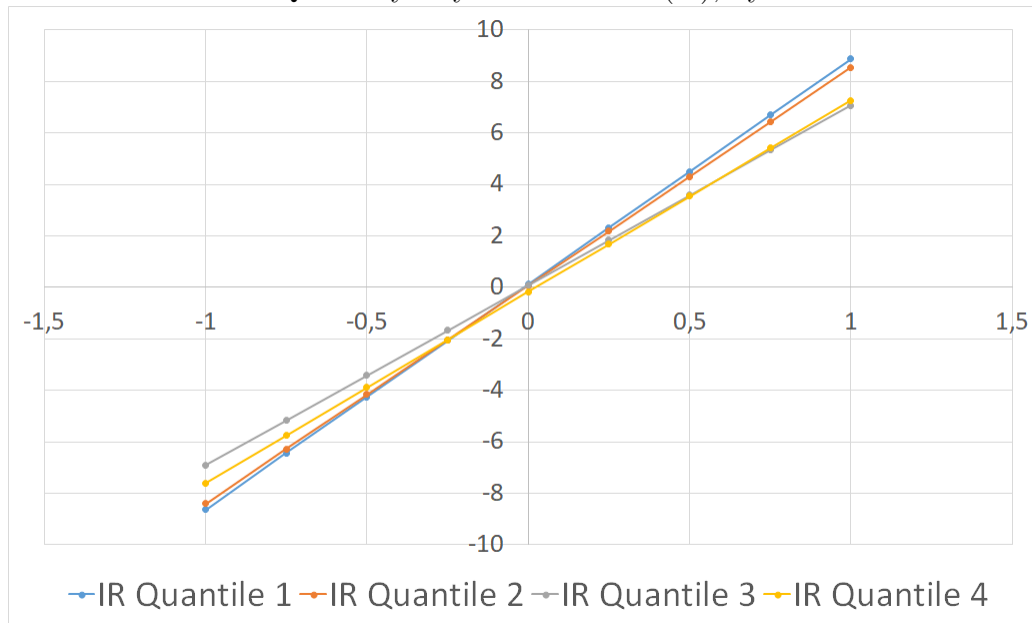
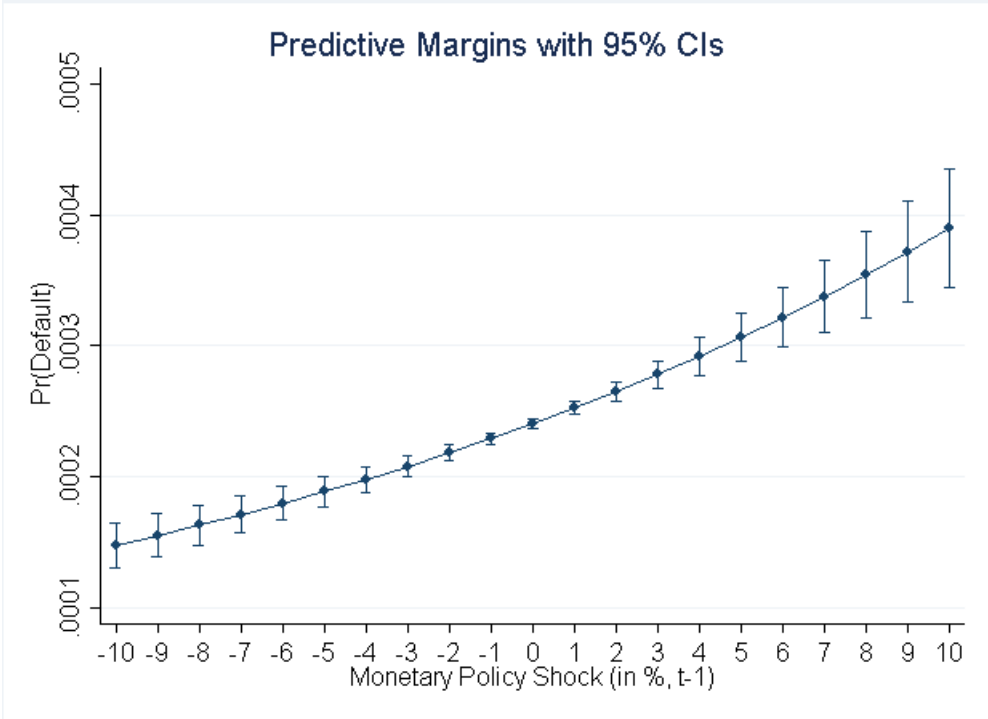


Figure 3.11: Predicted $Pr(Default)$, by Monetary Policy Shocks



10 Tables

Table 3.1: Descriptive Statistics: T-test (Default vs Healthy)

	(1)		(2)		(3)	
	<i>Defaulted</i>		<i>Healthy</i>		<i>Difference</i>	
	mean	sd	mean	sd	b	t
Quarterly Payment (%)	-0.02	0.89	-0.03	0.78	-0.00	(-1.61)
Annual Interest Rate (% , Origination)	4.23	1.02	3.95	1.07	-0.27***	(-192.81)
Quarterly Total Payment (€)	2,509.09	1,919.27	2,521.18	1,726.06	12.09***	(4.38)
Loan Size (Origination)	132,878.05	113,871.44	126,442.49	103,326.26	-6,435.56***	(-41.41)
Loan Duration (Years, Origination)	18.45	4.90	16.88	5.05	-1.57***	(-234.82)
Down-payment Rate (% , Origination)	9.62	17.73	18.56	22.89	8.94***	(368.38)
Down-payment Amount (€, Origination)	10,291.91	24,162.93	19,151.75	30,433.05	8,859.83***	(267.91)
DTI (Origination)	3.24	2.09	3.54	2.21	0.30***	(104.00)
LTV (Origination)	0.90	0.18	0.81	0.23	-0.09***	(-368.38)
Credit Rating (PD)	2.33	1.03	1.57	0.79	-0.76***	(-536.37)
Number of Other Outstanding Debts (Origination)	1.01	1.28	0.80	1.16	-0.21***	(-118.45)
Annual Income (Origination)	52,583.43	62,413.25	46,669.51	112,492.45	-5,913.91***	(-68.82)
Average Age of Debtors (Origination)	39.02	9.27	39.05	9.54	0.04**	(2.82)
Observations	540,029		74,446,744		74,986,773	

Table 3.2: Descriptive Statistics: T-test (Adjustable vs Fixed)

	(1)		(2)		(3)	
	<i>Adjustable</i>		<i>Fixed</i>		<i>Difference</i>	
	mean	sd	mean	sd	b	t
Quarterly Payment (%)	-0.40	3.06	0.00	0.00	0.40***	(283.58)
Annual Interest Rate (% , Origination)	3.93	1.74	3.96	0.99	0.02***	(29.58)
Quarterly Total Payment (€)	2,736.91	1,890.77	2,504.00	1,712.75	-232.91***	(-267.64)
Loan Size (Origination)	148,752.75	127,903.75	124,341.01	100,468.90	-24,411.74***	(-476.30)
Loan Duration (Years)	17.92	5.15	16.79	5.03	-1.13***	(-538.16)
Down-payment Rate (Origination)	13.48	20.32	18.98	23.04	5.50***	(655.60)
Down-payment Amount (€, Origination)	15,899.22	30,785.58	19,395.50	30,346.72	3,496.28***	(278.95)
DTI (Origination)	3.68	2.33	3.53	2.20	-0.15***	(-158.93)
LTV (Origination)	0.87	0.20	0.81	0.23	-0.05***	(-655.60)
Credit Rating (PD)	2.07	0.99	1.53	0.76	-0.54***	(-1,372.53)
Number of Other Outstanding Debts	0.94	1.23	0.79	1.16	-0.15***	(-306.35)
Annual Income (Origination)	51,912.38	66,832.81	46,210.47	115,641.19	-5,701.91***	(-193.04)
Average Age of Debtors (Origination)	39.54	9.47	39.00	9.54	-0.53***	(-137.58)
Observations	6,598,403		68,387,839		74,986,242	

Table 3.3: Share of Default Loans by Credit Ratings

	Credit Rating (A)	Credit Rating (B)	Credit Rating (C)	Credit Rating (D)	Total
No Default	2,137,422	1,130,740	259,278	141,371	3,668,811
	58.26	30.82	7.07	3.85	100.00
	99.68	98.94	97.72	95.64	99.15
Default	6,929	12,111	6,036	6,446	31,522
	21.98	38.42	19.15	20.45	100.00
	0.32	1.06	2.28	4.36	0.85
Total	2,144,351	1,142,851	265,314	147,817	3,700,333
	57.95	30.89	7.17	3.99	100.00
	100.00	100.00	100.00	100.00	100.00

Table 3.4: Default, Adjustable Loans and Contractionary Monetary Policy

	(1)	(2)	(3)	(4)
LTV (Origin) $\in] 0.6$	Ref.	Ref.	Ref.	Ref.
LTV (Origin) $\in 0.6, 0.8$	1.442*** (0.036)	1.426*** (0.035)	1.390*** (0.036)	1.138*** (0.031)
LTV (Origin) $\in 0.8, 1$	2.278*** (0.049)	2.219*** (0.048)	2.110*** (0.048)	1.310*** (0.033)
LTV (Origin) ≥ 1	3.253*** (0.068)	3.107*** (0.065)	2.966*** (0.064)	1.359*** (0.035)
Fixed Rate	Ref.	Ref.	Ref.	Ref.
Adjustable Rate (ADJ)	1.240*** (0.019)	1.297*** (0.020)	1.187*** (0.025)	0.699*** (0.015)
Expansionary MP			Ref.	Ref.
Contractionary MP			0.981 (0.018)	0.966 (0.018)
ADJ \times Contractionary MP			1.095** (0.037)	1.128*** (0.038)
Controls	No	No	No	Yes
Department Fixed Effect	No	Yes	Yes	Yes
Time Fixed Effect	No	Yes	Yes	Yes
Loans Types	All	All	All	All
Period	2004-15	2004-15	2004-15	2004-15
Pseudo R2	0.011	0.018	0.020	0.053
Observations	63,001,397	62,999,029	58,518,231	57,343,931

Controls include: maturity, quarter of the credit life, type of housing project, rating, number of other outstanding debts, household age and department unemployment. Exponentiated coefficients; Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.5: Loan Default: Impact of a Monetary Policy Shock

	(1)	(2)	(3)
Quarterly Payment Growth (%)	1.023*** (0.007)	1.039*** (0.007)	1.050*** (0.006)
LTV (Origin) \in 0.6-0.8	1.434*** (0.036)	1.388*** (0.036)	1.143*** (0.032)
LTV (Origin) \in 0.8-1	2.422*** (0.052)	2.086*** (0.048)	1.307*** (0.034)
LTV (Origin) \geq 1	3.712*** (0.076)	2.970*** (0.066)	1.375*** (0.036)
Current LTV \in 0.2-0.4		0.944*** (0.017)	1.126*** (0.022)
Current LTV \in 0.4-0.6		0.923*** (0.017)	1.160*** (0.027)
Current LTV \in 0.6-0.8		0.935*** (0.018)	1.275*** (0.034)
Current LTV \in 0.8-1		1.242*** (0.023)	1.742*** (0.050)
Current LTV \geq 1		1.564*** (0.038)	1.968*** (0.066)
Credit Rating = B			2.913*** (0.047)
Credit Rating = C			5.642*** (0.112)
Credit Rating = D			10.046*** (0.208)
Number of Other Outstanding Debts			1.049*** (0.005)
Log(Household Income)			0.934*** (0.010)
Average Age of Debtors (Origination)			1.008*** (0.001)
Maturity 11-15 years			0.912*** (0.019)
Maturity 16-20 years			0.947** (0.023)
Maturity \geq 20 years			1.042 (0.029)
Rental Property			0.894*** (0.014)
Secondary Residence			0.927** (0.029)
Age of Loan (in Quarters)			1.026*** (0.001)
Unemployment Rate Growth (%)			0.996* (0.002)
Department Fixed Effect		No	Yes
Time Fixed Effect	153	No	Yes
Loans Types		All	All
Period		2004-15	2004-15
Pseudo R2		0.012	0.020
Observations	60 560 076	57 149 077	55 988 009

Table 3.6: Loan Default: Heterogeneous Effects of Monetary Policy

	(1)	(2)	(3)	(4)
Quarterly Payment Growth (%)	1.045** (0.021)	1.044*** (0.007)	1.015* (0.008)	1.003 (0.009)
Current LTV \in 0.2-0.4	1.126*** (0.022)	1.123*** (0.022)	1.127*** (0.022)	1.124*** (0.022)
Current LTV \in 0.4-0.6	1.160*** (0.027)	1.156*** (0.027)	1.162*** (0.027)	1.158*** (0.027)
Current LTV \in 0.6-0.8	1.275*** (0.034)	1.270*** (0.034)	1.277*** (0.034)	1.272*** (0.034)
Current LTV \in 0.8-1	1.742*** (0.050)	1.733*** (0.050)	1.738*** (0.050)	1.730*** (0.050)
Current LTV \geq 1.0	1.969*** (0.066)	1.958*** (0.066)	1.959*** (0.066)	1.950*** (0.066)
Current LTV \in 0.2-0.4 \times Quarterly Payment Growth (%)	1.004 (0.025)			
Current LTV \in 0.4-0.6 \times Quarterly Payment Growth (%)	1.001 (0.023)			
Current LTV \in 0.6-0.8 \times Quarterly Payment Growth (%)	0.994 (0.023)			
Current LTV \in 0.8-1 \times Quarterly Payment Growth (%)	1.019 (0.025)			
Current LTV \geq 1 \times Quarterly Payment Growth (%)	1.041 (0.034)			
Vulnerable		1.074*** (0.015)		1.075*** (0.015)
Vulnerable \times Quarterly Payment Growth (%)		1.020 (0.013)		1.039** (0.017)
Unemployment Rate Growth (%)	0.996* (0.002)	0.996* (0.002)	0.997 (0.002)	0.999 (0.003)
Unemployment Rate Growth (%) \times Quarterly Payment Growth (%)			1.011*** (0.002)	1.012*** (0.002)
Vulnerable \times Unemployment Rate Growth (%)				0.994 (0.004)
Vulnerable \times Quarterly Payment Growth (%) \times Unemp Rate Growth (%)				0.994* (0.003)
Controls	Yes	Yes	Yes	Yes
Department Fixed Effect	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Loans Types	All	All	All	All
Period	2004-15	2004-15	2004-15	2004-15
Pseudo R2	0.052	0.052	0.052	0.052
Observations	55,988,009	55,988,009	55,988,009	55,988,009

Controls include: maturity, quarter of the credit life, type of housing project, rating, number of other outstanding debts, household age.

Exponentiated coefficients; Standard errors in parentheses

* p_i0.10, ** p_i0.05, *** p_i0.01

Table 3.7: Descriptive Statistics: Vulnerable Households

	No Vulnerable	Vulnerable	Total
No Default	2,762,027	906,784	3,668,811
	75.28	24.72	100
	99.22	98.94	99.15
Default	21,833	9,689	31,522
	69.26	30.74	100
	0.78	1.06	0.85
Total	2,783,860	916,473	3,700,333
	75.23	24.77	100
	100	100	100

Table 3.8: Loan Default: Robustness Checks

	(1)	(2)	(3)	(4)
Quarterly Payment Growth (%)	1.057*** (0.007)	1.045*** (0.007)	1.019* (0.010)	0.0000216*** (0.000)
Current LTV < 0.2	Ref.	Ref.	Ref.	Ref.
Current LTV ∈ (0.2-0.4)	0.976 (0.025)	0.671*** (0.035)	1.266*** (0.078)	0.0000676*** (0.000)
Current LTV ∈ (0.4-0.6)	1.016 (0.028)	0.667*** (0.032)	1.126 (0.088)	0.0000865*** (0.000)
Current LTV ∈ (0.6-0.8)	1.089*** (0.032)	0.760*** (0.036)	1.031 (0.102)	0.0001122*** (0.000)
Current LTV ∈ (0.8-1.0)	1.587*** (0.049)	1.177*** (0.056)	1.536*** (0.183)	0.0002413*** (0.000)
Current LTV > 1.0	1.882*** (0.067)	1.443*** (0.076)	2.454*** (0.344)	0.0003315*** (0.000)
LTV (Origin) < 0.6	Ref.	Ref.	Ref.	Ref.
LTV (Origin) ∈ (0.6-0.8)	1.196*** (0.040)	0.917* (0.046)	0.823** (0.075)	0.0000127* (0.000)
LTV (Origin) ∈ (0.8-1)	1.342*** (0.041)	0.955 (0.045)	1.038 (0.086)	0.0000371*** (0.000)
LTV (Origin) > 1	1.410*** (0.043)	1.000 (0.048)	0.899 (0.076)	0.0000618*** (0.000)
Controls	Yes	Yes	Yes	Yes (OLS)
Time Fixed Effect	Yes	Yes	Yes	Yes (OLS)
Department Fixed Effect	Yes	Yes	Yes	Yes (OLS)
Loans Types	First 7 Yrs	First 7, 20+ years	Adj Only	All
Period	2004-15	2004-15	2004-15*	2004-15
Pseudo R2	0.060	0.057	0.064	0.053
Observations	44,757,278	20,375,829	1,828,000	87,147,867

Controls: maturity, quarter of the credit life, type of housing project, rating, number of other outstanding debts, household age and department unemployment. Exponentiated coefficients. Standard errors in parentheses.

* During years of continuous falling policy rates. * 0.10, ** 0.05, *** 0.01

A The Bias of Adjustable Rate Loans

A substantial number of adjustable credit lines are lost during the process of data cleaning and amortization tables reconstruction. Thus, we do not work with the true population but a sample of the original data. This is not problematic if a proper process of random selection is applied. Nevertheless, this is not our case, since most of our discarded data refers to adjustable loans, and fixed rate loans are mostly unaffected. The resulting sample is a non-randomized fraction of the original data and it may bias subsequent estimation results on default probability. The direction of the bias depends on the resulting defaults distribution.

Average default probabilities \overline{D} conditional on the type of interest rate (*Adjustable*) in the true population are equal to:

$$\overline{D}|_{Adjustable=1} = \beta_0 + \beta_1$$

$$\overline{D}|_{Adjustable=0} = \beta_0$$

where the true population relationship is $D_{it} = \beta_0 + \beta_1 Adjustable_i$.

Using the non-random sample, the estimated equation of the true relationship is represented as:

$$D_{it} = \hat{\beta}_0 + \hat{\beta}_1 Adjustable_i + \epsilon_{it}$$

where,

$$\mathbb{E}(D|_{adjustable=0}) = \hat{\beta}_0 = \overline{D}|_{Adjustable=0}$$

$$\mathbb{E}(D|_{adjustable=1}) = \hat{\beta}_0 + \hat{\beta}_1 \neq \overline{D}|_{Adjustable=1}$$

The estimated expected value of default for fixed rate loans using the non-random sample is equal to the true population average, which indicates that the estimates of β_0 are unbiased. Nevertheless, the expected default of adjustable loans differs from the true population mean. Since β_0 is consistently estimated, the source of bias must be a change on the distribution of defaults for adjustable loans. In other words, defaults within the adjustable group are not missing at random. In particular, comparisons between original data and the resulting sample show that default probability of adjustable rate loans of our sample is lower than in the original population, such that $\hat{\beta}_1$ and the subsequent odd ratio are underestimated:

$$\hat{\beta}_1 < \beta_1$$

$$OddRatio = \frac{\beta_0 + \hat{\beta}_1}{\beta_0} < \frac{\beta_0 + \beta_1}{\beta_0}$$

B Reconstructing Amortisation Tables

In this appendix we aim at detailing the process of re-construction of amortisation tables presented in section 3.1 with examples. We choose a 200,000€ loan with 20 years maturity and a starting interest rate of 4.1%. Then, we simulate a conventional loan payment table for two different adjustment schedules: fixed and adjustable. Starting from a complete information table, we do drop all elements which are not available in our real data set and

we apply our reconstruction methodology step by step. We do simulate a loan in order to be able to compare final computations with initial ones. Our lack of certain variables would not have allowed such a comparison using our data set.

Fixed Rate Loans FRL Table 3.9 presents the complete amortisation table of the chosen loan example for a fixed rate schedule computed as if we were the borrower. Interest rate R and total payments M are constant over the entire loan life, such that the monetary policy shock is always equal to 0.

Table 3.9: FRL amortisation table - 200k, 20 years, 4.1% started in 2004q1

Quarter	Date	Interest Rate (R)	Outstanding Principal	Principal payment (P)	Interest payment (I)	Total payment (M)	MP shock
1	2004q1	4.1	200,000.0 €	1,625.6 €	2,050.0 €	3,675.6 €	
2	2004q2	4.1	198,374.4 €	1,642.3 €	2,033.3 €	3,675.6 €	0.0 €
3	2004q3	4.1	196,732.1 €	1,659.1 €	2,016.5 €	3,675.6 €	0.0 €
4	2004q4	4.1	195,072.9 €	1,676.1 €	1,999.5 €	3,675.6 €	0.0 €
5	2005q1	4.1	193,396.8 €	1,693.3 €	1,982.3 €	3,675.6 €	0.0 €
6	2005q2	4.1	191,703.5 €	1,710.7 €	1,965.0 €	3,675.6 €	0.0 €
7	2005q3	4.1	189,992.8 €	1,728.2 €	1,947.4 €	3,675.6 €	0.0 €
8	2005q4	4.1	188,264.6 €	1,745.9 €	1,929.7 €	3,675.6 €	0.0 €
9	2006q1	4.1	186,518.6 €	1,763.8 €	1,911.8 €	3,675.6 €	0.0 €
10	2006q2	4.1	184,754.8 €	1,781.9 €	1,893.7 €	3,675.6 €	0.0 €
...
40	2013q4	4.1	122,537.1 €	2,419.6 €	1,256.0 €	3,675.6 €	0.0 €
41	2014q1	4.1	120,117.5 €	2,444.4 €	1,231.2 €	3,675.6 €	0.0 €
42	2014q2	4.1	117,673.0 €	2,469.5 €	1,206.1 €	3,675.6 €	0.0 €
43	2014q3	4.1	115,203.5 €	2,494.8 €	1,180.8 €	3,675.6 €	0.0 €
44	2014q4	4.1	112,708.7 €	2,520.4 €	1,155.3 €	3,675.6 €	0.0 €
45	2015q1	4.1	110,188.4 €	2,546.2 €	1,129.4 €	3,675.6 €	0.0 €
46	2015q2	4.1	107,642.2 €	2,572.3 €	1,103.3 €	3,675.6 €	0.0 €
47	2015q3	4.1	105,069.9 €	2,598.7 €	1,077.0 €	3,675.6 €	0.0 €
48	2015q4	4.1	102,471.2 €	2,625.3 €	1,050.3 €	3,675.6 €	0.0 €

Table 3.10 represents the exact information we do observe in our data. Hence, interest rates and quarterly payments are omitted in order to simulate the exact data conditions we face in our paper.

Table 3.10: FRL Amortisation Table - Step 0

Quarter	Date	Interest Rate (R)	Outstanding Principal	Principal payment (P)	Interest payment (I)	Total payment (M)	MP shock
1	2004q1		200,000.0 €				
2	2004q2		198,374.4 €				
3	2004q3		196,732.1 €				
4	2004q4		195,072.9 €				
5	2005q1		193,396.8 €				
6	2005q2		191,703.5 €				
7	2005q3		189,992.8 €				
8	2005q4		188,264.6 €				
9	2006q1		186,518.6 €				
10	2006q2		184,754.8 €				
...
40	2013q4		122,537.1 €				
41	2014q1		120,117.5 €				
42	2014q2		117,673.0 €				
43	2014q3		115,203.5 €				
44	2014q4		112,708.7 €				
45	2015q1		110,188.4 €				
46	2015q2		107,642.2 €				
47	2015q3		105,069.9 €				
48	2015q4		102,471.2 €				

We now apply the reconstruction process presented in section 3.1. Results are presented in Table 3.11. First, we compute principal payments at each quarter P_t . Second, we apply the following formula,

$$R = \frac{\Delta P}{P_{t-1}} \quad (3.4)$$

Table 3.11: FRL Amortisation table - Steps 1 and 2

Quarter	Date	Second		First			
		Interest Rate (R)	Outstanding Principal	Principal payment (P)	Interest payment (I)	Total payment (M)	MP shock
1	2004q1	4.1	200,000.0 €	1,625.6 €			
2	2004q2	4.1	198,374.4 €	1,642.3 €			
3	2004q3	4.1	196,732.1 €	1,659.1 €			
4	2004q4	4.1	195,072.9 €	1,676.1 €			
5	2005q1	4.1	193,396.8 €	1,693.3 €			
6	2005q2	4.1	191,703.5 €	1,710.7 €			
7	2005q3	4.1	189,992.8 €	1,728.2 €			
8	2005q4	4.1	188,264.6 €	1,745.9 €			
9	2006q1	4.1	186,518.6 €	1,763.8 €			
10	2006q2	4.1	184,754.8 €	1,781.9 €			
...			
40	2013q4	4.1	122,537.1 €	2,419.6 €			
41	2014q1	4.1	120,117.5 €	2,444.4 €			
42	2014q2	4.1	117,673.0 €	2,469.5 €			
43	2014q3	4.1	115,203.5 €	2,494.8 €			
44	2014q4	4.1	112,708.7 €	2,520.4 €			
45	2015q1	4.1	110,188.4 €	2,546.2 €			
46	2015q2	4.1	107,642.2 €	2,572.3 €			
47	2015q3	4.1	105,069.9 €	2,598.7 €			
48	2015q4	4.1	102,471.2 €	2,625.3 €			

Finally, since we know the loan maturity and we computed the interest rate, we can easily fill in remaining gaps using classic amortisation table formulas. The result of our reconstructed table is presented in Table 3.12. As observed, we exactly reproduced the original fixed rate loan schedule presented in Table 3.9, which evidences the validity of our methodology to reconstruct missing information, interest rates and the monetary policy shock in this case.

Table 3.12: FRL Amortisation Table - Step 3

Quarter	Date	Second		First		Third	Third	Third
		Interest Rate (R)	Outstanding Principal	Principal payment (P)	Interest payment (I)	Total payment (M)	MP shock	
1	2004q1	4.1	200,000.0 €	1,625.6 €	2,050.0 €	3,675.6 €		
2	2004q2	4.1	198,374.4 €	1,642.3 €	2,033.3 €	3,675.6 €	0.0 €	
3	2004q3	4.1	196,732.1 €	1,659.1 €	2,016.5 €	3,675.6 €	0.0 €	
4	2004q4	4.1	195,072.9 €	1,676.1 €	1,999.5 €	3,675.6 €	0.0 €	
5	2005q1	4.1	193,396.8 €	1,693.3 €	1,982.3 €	3,675.6 €	0.0 €	
6	2005q2	4.1	191,703.5 €	1,710.7 €	1,965.0 €	3,675.6 €	0.0 €	
7	2005q3	4.1	189,992.8 €	1,728.2 €	1,947.4 €	3,675.6 €	0.0 €	
8	2005q4	4.1	188,264.6 €	1,745.9 €	1,929.7 €	3,675.6 €	0.0 €	
9	2006q1	4.1	186,518.6 €	1,763.8 €	1,911.8 €	3,675.6 €	0.0 €	
10	2006q2	4.1	184,754.8 €	1,781.9 €	1,893.7 €	3,675.6 €	0.0 €	
...	
40	2013q4	4.1	122,537.1 €	2,419.6 €	1,256.0 €	3,675.6 €	0.0 €	
41	2014q1	4.1	120,117.5 €	2,444.4 €	1,231.2 €	3,675.6 €	0.0 €	
42	2014q2	4.1	117,673.0 €	2,469.5 €	1,206.1 €	3,675.6 €	0.0 €	
43	2014q3	4.1	115,203.5 €	2,494.8 €	1,180.8 €	3,675.6 €	0.0 €	
44	2014q4	4.1	112,708.7 €	2,520.4 €	1,155.3 €	3,675.6 €	0.0 €	
45	2015q1	4.1	110,188.4 €	2,546.2 €	1,129.4 €	3,675.6 €	0.0 €	
46	2015q2	4.1	107,642.2 €	2,572.3 €	1,103.3 €	3,675.6 €	0.0 €	
47	2015q3	4.1	105,069.9 €	2,598.7 €	1,077.0 €	3,675.6 €	0.0 €	
48	2015q4	4.1	102,471.2 €	2,625.3 €	1,050.3 €	3,675.6 €	0.0 €	

Adjustable Rate Loans ARL Table 3.13 presents the complete amortisation table of the chosen loan example for an adjustable rate schedule computed as if we were the borrower. Interest rates R_t adjust every quarter following 3-month Euribor of the past quarter. Thus, total payments M vary over the entire loan life, such that the monetary policy shock depends on the magnitude of the change. For the sake of space, we only present a window of time around the quarters of stable Euribor evolution. As previously, Table 3.14 presents the example of the exact information we observe in our data set. Again, interest rates and payments are unknown and we apply our methodology to approximate them.

Table 3.13: ARL Amortisation Table - 200k, 20 years, 4.1% started in 2004q1

Quarter	Date	Euribor 3m t-1	Spread (S)	Interest Rate (R)	Outstanding Principal	Principal payment (P)	Interest payment (I)	Total payment (M)	MP shock
1	2004q1	2.15	1.95	4.10	200,000.0 €	1,625.6 €	2,050.0 €	3,675.6 €	
2	2004q2	2.06	1.95	4.01	198,374.4 €	1,658.5 €	1,988.7 €	3,647.2 €	-28.4 €
3	2004q3	2.08	1.95	4.03	196,715.8 €	1,671.6 €	1,981.9 €	3,653.5 €	6.2 €
4	2004q4	2.12	1.95	4.07	195,044.2 €	1,681.2 €	1,984.6 €	3,665.8 €	12.3 €
5	2005q1	2.16	1.95	4.11	193,363.0 €	1,691.3 €	1,986.8 €	3,678.1 €	12.2 €
6	2005q2	2.14	1.95	4.09	191,671.7 €	1,712.2 €	1,959.8 €	3,672.0 €	-6.1 €
7	2005q3	2.12	1.95	4.07	189,959.6 €	1,733.2 €	1,932.8 €	3,666.0 €	-6.0 €
8	2005q4	2.13	1.95	4.08	188,226.4 €	1,749.1 €	1,919.9 €	3,669.0 €	3.0 €
9	2006q1	2.34	1.95	4.29	186,477.3 €	1,730.6 €	2,000.0 €	3,730.6 €	61.6 €
10	2006q2	2.61	1.95	4.56	184,746.7 €	1,703.6 €	2,106.1 €	3,809.7 €	79.1 €
...
37	2013q1	0.20	1.95	2.15	129,994.5 €	2,626.7 €	698.7 €	3,325.4 €	-28.7 €
38	2013q2	0.21	1.95	2.16	127,367.7 €	2,639.4 €	687.8 €	3,327.2 €	1.8 €
39	2013q3	0.21	1.95	2.16	124,728.3 €	2,653.7 €	673.5 €	3,327.2 €	0.0 €
40	2013q4	0.22	1.95	2.17	122,074.7 €	2,666.6 €	662.3 €	3,328.9 €	1.7 €
41	2014q1	0.24	1.95	2.19	119,408.1 €	2,678.4 €	653.8 €	3,332.1 €	3.3 €
42	2014q2	0.30	1.95	2.25	116,729.7 €	2,685.1 €	656.6 €	3,341.7 €	9.6 €
43	2014q3	0.30	1.95	2.25	114,044.6 €	2,700.2 €	641.5 €	3,341.7 €	0.0 €
44	2014q4	0.16	1.95	2.11	111,344.3 €	2,733.1 €	587.3 €	3,320.4 €	-21.3 €
45	2015q1	0.08	1.95	2.03	108,611.2 €	2,757.4 €	551.2 €	3,308.6 €	-11.8 €
46	2015q2	0.05	1.95	2.00	105,853.9 €	2,775.0 €	529.3 €	3,304.3 €	-4.3 €
47	2015q3	-0.01	1.95	1.94	103,078.8 €	2,796.0 €	499.9 €	3,295.9 €	-8.4 €
48	2015q4	-0.03	1.95	1.92	100,282.9 €	2,811.8 €	481.4 €	3,293.2 €	-2.7 €

Table 3.14: ARL Amortisation Table - Step 0

Quarter	Date	Euribor 3m t-1	Spread (S)	Interest Rate (R)	Outstanding Principal	Principal payment (P)	Interest payment (I)	Total payment (M)	MP shock
1	2004q1	2.15			200,000.0 €				
2	2004q2	2.06			198,374.4 €				
3	2004q3	2.08			196,715.8 €				
4	2004q4	2.12			195,044.2 €				
5	2005q1	2.16			193,363.0 €				
6	2005q2	2.14			191,671.7 €				
7	2005q3	2.12			189,959.6 €				
8	2005q4	2.13			188,226.4 €				
9	2006q1	2.34			186,477.3 €				
10	2006q2	2.61			184,746.7 €				
...				
37	2013q1	0.20			129,994.5 €				
38	2013q2	0.21			127,367.7 €				
39	2013q3	0.21			124,728.3 €				
40	2013q4	0.22			122,074.7 €				
41	2014q1	0.24			119,408.1 €				
42	2014q2	0.30			116,729.7 €				
43	2014q3	0.30			114,044.6 €				
44	2014q4	0.16			111,344.3 €				
45	2015q1	0.08			108,611.2 €				
46	2015q2	0.05			105,853.9 €				
47	2015q3	-0.01			103,078.8 €				
48	2015q4	-0.03			100,282.9 €				

We now apply the reconstruction process presented in section 3.1. Results are presented in Table 3.15. First, we compute principal payments at each quarter P_t . Second, we apply the following formula only in periods of stable monetary policy (highlighted in bold in the second column),

$$R_t = \frac{\text{Principal}_{t-1} \times \Delta E_{t-1} + \Delta P - \Delta M}{P_{t-1}} \quad (3.5)$$

Importantly, we assume ΔM and ΔE_{t-1} to be closed to zero. Thus, we obtain an approximation of the interest rate for each period which is presented in column 6 (R temp). We observe some differences on the interest rate approximation between quarters. Subsequently, we compute the average interest rate of each time window (R mean).

Third, we compute the difference between the mean interest rate of the period and the 3-month Euribor in t-1. This gives us an approximation of the spread, which is presented

in column 4 (*S temp*). Since we know that the spread is constant over the entire loan life, we compute the mean using all spread approximations we just computed. The result is our best approximation of the true spread and corresponds to the column 5 of Table 3.15. Now, we can compute our time-varying approximation of interest rates following,

$$R_t = S + E_{t-1} \quad (3.6)$$

Table 3.15: ARL Amortisation Table - Steps 1, 2 and 3

Quarter	Date	E_{t-1}	Third S temp	Third Spread (S)	Second R temp	Second R mean	Third Interest Rate (R)	Outstanding Principal	First Principal pmnt (P)	Interest pmnt (I)	Total pmnt (M)	MP shock
1	2004q1	2.15	2.06	1.95		4.21	4.10	200,000.0 €	1,625.6 €			
2	2004q2	2.06	2.15	1.95	8.10	4.21	4.01	198,374.4 €	1,658.5 €			
3	2004q3	2.08	2.13	1.95	3.14	4.21	4.03	196,715.8 €	1,671.6 €			
4	2004q4	2.12	2.09	1.95	2.32	4.21	4.07	195,044.2 €	1,681.2 €			
5	2005q1	2.16	2.05	1.95	2.38	4.21	4.11	193,363.0 €	1,691.3 €			
6	2005q2	2.14	2.07	1.95	4.95	4.21	4.09	191,671.7 €	1,712.2 €			
7	2005q3	2.12	2.09	1.95	4.91	4.21	4.07	189,959.6 €	1,733.2 €			
8	2005q4	2.13	2.08	1.95	3.67	4.21	4.08	188,226.4 €	1,749.1 €			
9	2006q1	2.34		1.95			4.29	186,477.3 €	1,730.6 €			
10	2006q2	2.61		1.95			4.56	184,746.7 €	1,703.6 €			
...			
37	2013q1	0.20	1.75	1.95		1.95	2.15	129,994.5 €	2,626.7 €			
38	2013q2	0.21	1.74	1.95	1.93	1.95	2.16	127,367.7 €	2,639.4 €			
39	2013q3	0.21	1.74	1.95	2.16	1.95	2.16	124,728.3 €	2,653.7 €			
40	2013q4	0.22	1.73	1.95	1.95	1.95	2.17	122,074.7 €	2,666.6 €			
41	2014q1	0.24	1.71	1.95	1.77	1.95	2.19	119,408.1 €	2,678.4 €			
42	2014q2	0.30		1.95			2.25	116,729.7 €	2,685.1 €			
43	2014q3	0.30		1.95			2.25	114,044.6 €	2,700.2 €			
44	2014q4	0.16		1.95			2.11	111,344.3 €	2,733.1 €			
45	2015q1	0.08		1.95			2.03	108,611.2 €	2,757.4 €			
46	2015q2	0.05		1.95			2.00	105,853.9 €	2,775.0 €			
47	2015q3	-0.01		1.95			1.94	103,078.8 €	2,796.0 €			
48	2015q4	-0.03		1.95			1.92	100,282.9 €	2,811.8 €			

Finally, once we approximate the spread S and the interest rate R_t , we can fill in the payments information as we did previously. The full approximated amortisation table is presented in Figure 3.16. If we compare our approximation to the original amortisation table, we observe that differences start at the third decimal of the spread. Nevertheless, the bias can be more important in magnitude depending on the loan size, maturity and date of start. A more detail analysis of the bias and its sources is presented in section 3.2.

Table 3.16: ARL Amortisation Table - Step 4

Quarter	Date	E_{t-1}	Third S temp	Third Spread (S)	Second R temp	Second R mean	Third Interest Rate (R)	Outstanding	Principal	First Principal pmnt (P)	Four Interest pmnt (I)	Four Total pmnt (M)	Four MP shock
1	2004q1	2.15	2.06	1.95		4.21	4.10	200,000.0 €		1,625.6 €	2,051.5 €	3,676.6 €	
2	2004q2	2.06	2.15	1.95	8.10	4.21	4.01	198,374.4 €		1,658.5 €	1,990.2 €	3,648.2 €	-28.4 €
3	2004q3	2.08	2.13	1.95	3.14	4.21	4.03	196,715.8 €		1,671.6 €	1,983.4 €	3,654.4 €	6.2 €
4	2004q4	2.12	2.09	1.95	2.32	4.21	4.07	195,044.2 €		1,681.2 €	1,986.0 €	3,666.7 €	12.3 €
5	2005q1	2.16	2.05	1.95	2.38	4.21	4.11	193,363.0 €		1,691.3 €	1,988.2 €	3,679.0 €	12.2 €
6	2005q2	2.14	2.07	1.95	4.95	4.21	4.09	191,671.7 €		1,712.2 €	1,961.3 €	3,672.9 €	-6.1 €
7	2005q3	2.12	2.09	1.95	4.91	4.21	4.07	189,959.6 €		1,733.2 €	1,934.3 €	3,666.9 €	-6.0 €
8	2005q4	2.13	2.08	1.95	3.67	4.21	4.08	188,226.4 €		1,749.1 €	1,921.3 €	3,669.9 €	2.9 €
9	2006q1	2.34		1.95			4.29	186,477.3 €		1,730.6 €	2,001.4 €	3,731.5 €	61.6 €
10	2006q2	2.61		1.95			4.56	184,746.7 €		1,703.6 €	2,107.5 €	3,810.6 €	79.1 €
...
37	2013q1	0.20	1.75	1.95		1.95	2.15	129,994.5 €		2,626.7 €	699.7 €	3,326.0 €	-89.7 €
38	2013q2	0.21	1.74	1.95	1.93	1.95	2.16	127,367.7 €		2,639.4 €	688.7 €	3,327.7 €	1.7 €
39	2013q3	0.21	1.74	1.95	2.16	1.95	2.16	124,728.3 €		2,653.7 €	674.5 €	3,327.7 €	0.0 €
40	2013q4	0.22	1.73	1.95	1.95	1.95	2.17	122,074.7 €		2,666.6 €	663.2 €	3,329.4 €	1.7 €
41	2014q1	0.24	1.71	1.95	1.77	1.95	2.19	119,408.1 €		2,678.4 €	654.6 €	3,332.6 €	3.3 €
42	2014q2	0.30		1.95			2.25	116,729.7 €		2,685.1 €	657.5 €	3,342.2 €	9.6 €
43	2014q3	0.30		1.95			2.25	114,044.6 €		2,700.2 €	642.4 €	3,342.2 €	0.0 €
44	2014q4	0.16		1.95			2.11	111,344.3 €		2,733.1 €	588.2 €	3,320.9 €	-21.3 €
45	2015q1	0.08		1.95			2.03	108,611.2 €		2,757.4 €	552.0 €	3,309.0 €	-11.8 €
46	2015q2	0.05		1.95			2.00	105,853.9 €		2,775.0 €	530.1 €	3,304.7 €	-4.3 €
47	2015q3	-0.01		1.95			1.94	103,078.8 €		2,796.0 €	500.7 €	3,296.3 €	-8.4 €
48	2015q4	-0.03		1.95			1.92	100,282.9 €		2,811.8 €	482.1 €	3,293.6 €	-2.7 €

Conclusion Générale

Au lendemain de la crise financière, la littérature académique considérait les activités “traditionnelles” de l’assurance comme étant toujours incapables de générer un événement systémique à elles seules. Néanmoins, les renflouements à grande échelle pour des assureurs comme AIG ou Aegon dans le sillage de 2008—ainsi que la vague de faillites japonaises au cours de la décennie dite “perdue”—ont démontré que ce secteur était vulnérable aux chocs macroéconomiques provenant de l’extérieur de ce secteur.

Cette idée s’est concrétisée dans plusieurs évolutions réglementaires importantes qui ont transformé le marché européen de l’assurance depuis la grande récession, avec une attention particulière sur la mise en place d’exigences de fonds propres qui sont cohérentes avec le marché (*market-consistent*) et fondées sur le risque (*risk-based*). En parallèle, d’autres transformations réglementaires ont servi à ouvrir la concurrence pour certaines branches d’activité spécifiques, intensifiant ainsi les pressions du marché notamment sur les organismes de petite ou moyenne taille.

Face à ces évolutions, l’objectif de cette thèse est de comprendre les effets des nouvelles normes réglementaires sur le marché de l’assurance, et de mettre en évidence la dynamique des défaillances lorsqu’elles se produisent. L’analyse de défaut est également au coeur du dernier chapitre, qui porte sur les prêts au logement. L’analyse de ces trois questions—l’effet des réformes réglementaires, la défaillance des organismes d’assurance et le défaut des prêts immobiliers—constituent les trois chapitres de cette thèse.

Principaux Résultats, Implications de Supervision Prudentielle et Possibles Extensions

Les résultats du **premier chapitre** présentent un intérêt particulier pour la supervision prudentielle des organismes d’assurance. Il est fondé sur une base de données unique

construite manuellement pour identifier les déterminants des défaillances assurantielles, ses dynamiques temporelles et ses différences d'une juridiction à l'autre.

Nos résultats empiriques reposent sur l'estimation des modèles logistiques avec divers régimes d'effets fixes—ainsi que des modèles de survie—pour fournir de nouvelles contributions à la littérature sur l'insolvabilité des assureurs. Nous montrons que la composition du portefeuille (en termes de classe d'actifs) est importante pour la prévention de l'insolvabilité sur le marché de l'assurance vie, à la différence du marché de l'assurance non-vie. Les instruments à revenu fixe contribuent ainsi à la survie de ces organismes. En revanche, l'efficacité opérationnelle (mesurée par le ratio des frais d'exploitation et d'administration sur le total des primes émises) ne joue aucun rôle dans le secteur vie mais apparaît cruciale dans le secteur non-vie. En rassemblant les institutions solvables et insolubles de plusieurs pays dans une seule base de données, nous sommes en mesure de mieux isoler les différences entre les secteurs ainsi qu'entre les juridictions nationales.

Pour les superviseurs, ce chapitre appelle à une attention accrue au risque de marché pour les organismes d'assurance-vie, avec un accent particulier sur les placements en actions ou en fonds d'investissement. En effet, ces instruments sont déjà soumis à des exigences de fonds propres plus élevées dans la plupart des juridictions et ont généralement une moindre présence dans le portefeuille des assureurs par rapport aux instruments de dette.

Cette analyse présente néanmoins plusieurs limites importantes. Premièrement, notre base de données est un panel déséquilibré qui est influencé par la surreprésentation des entreprises américaines. Par ailleurs, la période d'étude constitue un environnement de baisse quasi continue des taux d'intérêt ; dans ce cas particulier, les anciennes obligations gagnent en valeur de marché à mesure que les taux baissent. Il est également plus difficile d'identifier l'effet des variables macroéconomiques étant donné leur manque relatif de variation significative, en particulier lorsque l'on travaille avec des données de bilan annuelles (à basse fréquence). Les approches employées ici ne permettent pas de démêler cet effet mécanique (bénéfique) des propriétés intrinsèques de ces actifs. Enfin, nous aurions aimé approfondir l'analyse en menant une estimation des coûts de chaque défaillance ; cela nous aurait permis de comprendre comment les décisions de gestion prises en amont peuvent soit atténuer soit amplifier l'ampleur des défaillances lorsqu'elles se matérialisent. En raison d'un manque de données suffisantes, cela a été laissé pour des recherches futures.

Le **deuxième chapitre** étudie la transformation du marché français de l'assurance du-

rant la période de 2011 à 2019, au cours de laquelle plusieurs réformes réglementaires sont entrées en vigueur. Un premier résultat de cet article consiste à montrer une prédominance des fusions classiques, c'est-à-dire celles qui cherchent à réaliser des économies d'échelle au sein des branches d'activités similaires. Ce résultat est cohérent avec une absence d'arbitrage réglementaire ; les assureurs ne semblent pas rechercher d'autres assureurs aux profils de risque opposés, dans le but de diversifier les risques et de bénéficier ainsi de la conception de la formule standard de Solvabilité II. Nous analysons ensuite une réforme spécifique à la santé (la loi ANI) et constatons une forte vague de fusions dans ce secteur. En exploitant le fait que seul un segment du marché français était exposé à cette loi, nous montrons que les assureurs "cibles" dans cette ligne d'activité n'étaient pas motivés dans l'immédiat par des soucis de rentabilité, contrairement aux fusions au sein d'autres branches. Ce résultat pourrait s'expliquer par le fait que ces organismes avaient prévu la réforme avant la matérialisation de ses conséquences. Enfin, nous montrons que, malgré une forte augmentation de l'activité MA depuis 2011, les indices de concentration du marché restent très faibles dans la quasi-totalité des lignes d'activité, impliquant que les assurés bénéficient toujours d'un marché concurrentiel pour de nombreux types de contrats d'assurance.

L'analyse de cet article a également souffert de certaines contraintes liées à la disponibilité des données. En effet, nous voulions dans un premier temps approfondir la question des fusions intra-branches. S'il était possible de reconstituer les différentes composantes du SCR avant l'ère de Solvabilité II, cela aurait permis d'identifier l'effet de l'entrée en vigueur de ce règlement. Cependant, ces formules sont trop sophistiquées pour être approximées à l'aide des données Solvabilité I disponibles. Ainsi, il a fallu se contenter d'un graphique de corrélation montrant la prédominance des fusions inter-branches pour conclure sur la question. Des extensions possibles à ce chapitre incluent l'utilisation d'une variable instrumentale pour identifier l'exposition précise de chaque organisme au choc réglementaire (même si des effets d'annonce des années en amont l'entrée en vigueur compliqueraient une telle approche). Enfin, les données au niveau des contrats permettraient de comprendre si ces réformes (ou les fusions qui ont eu lieu en parallèle) ont entraîné des changements de prix sur le marché des produits, ou bien une dégradation en qualité.

Le **troisième chapitre** aborde un marché distinct—les prêts au logement—mais reste sur le thème de la prédiction de défaut. En particulier, nous étudions l'impact des changements de politique monétaire sur le défaut des crédits immobiliers sur la période 2004-2015. Le résultat principal consiste à démontrer qu'une augmentation de 100 points de base du paiement trimestriel induite par les variations de l'Euribor 3 mois augmente la probabilité

de défaut d'environ 5%. De plus, nous identifions la stabilité de l'emploi comme un facteur d'assurance majeur contre ce type d'exposition au risque de taux d'intérêt inhérent aux prêts à taux variable.

Plusieurs caractéristiques de notre jeu de données propriétaire renforcent la contribution de ce chapitre. D'abord, il présente une absence de défaut stratégique, ce qui isole le défaut involontaire dans nos estimations. Ce trait diffère des données comparables générées par la juridiction américaine, dans laquelle les ménages submergés trouvent souvent une incitation à abandonner leur bien. En revanche, une limite de ces données réside dans la sous-représentation des prêts à taux variable (l'objet même de l'étude). De plus, même si nous disposons de la catégorie socio-économique des emprunteurs, notre variable capturant la fragilité des catégories vulnérables reste quelque peu spéculative. Par ailleurs, cette analyse pourrait être étendue au-delà de la France, en particulier dans les pays où la présence de prêts variables est plus élevée, afin de mieux comprendre comment le défaut interagit avec les taux de politique monétaire.